ESSAYS ON REGULATION AND ITS IMPACT ON INDUSTRY AND TAXATION: STUDIES ON CAFE STANDARDS

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ESSAYS ON REGULATION AND ITS IMPACT ON INDUSTRY AND TAXATION: STUDIES ON CAFE STANDARDS

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Abstract: Adopted in 1975, Corporate Average Fuel Economy (CAFE) standards had profound influences on the automobile industry as well as fleet fuel economy in the United States. In my dissertation, I first looked into the historical impacts of CAFE standards in the automobile industry using vehicle attribute data. I found evidence that the increase in the stringency of CAFE standards can induce the innovation of fuel economy related technologies in the automobile industry. I further estimated the response rate of the induced innovation with respect to stringency increases in CAFE standards. Using these estimates, I predicted that automobile companies would be able to meet the high 2025 fuel economy target by making medium downsizing in cars and minor downsizing in light duty trucks. Such methods can also be applied in other industries that have performance based regulations. CAFE standards increased fleet fuel economy in the United States as it was designed to. However, a more fuel efficient fleet resulted in less gasoline tax revenue, which is the major source of road maintenance. This trend affected governments at both federal and state levels. With more stringent CAFE standards enforced by the Obama Administration, which seek to almost double vehicle fuel economy by 2025, the gasoline tax revenue would be further eroded. As major increases

in the gasoline tax rate are not politically feasible in the United States, policy makers seek other methods, such as a vehicle mile traveled (VMT) tax, to maintain a more stable revenue flow. I estimated households' driving demand in response to driving cost changes using household survey data and estimated tax revenue under different tax scenarios. I showed that although a VMT tax can be more regressive than a gasoline tax, it provides more stable tax revenue without having to make major adjustments in tax rates when fleet fuel economy keeps increasing.

BIOGRAPHICAL SKETCH

Yiwei Wang joined the PhD program at the Dyson School of Applied Economics and Management at Cornell University in 2010. His research interest is in environmental economics, with a focus on environmental economics and policy using applied econometrics and quantitative analysis.

Yiwei graduated from Fudan University in Shanghai, China in 2002 with a Bachelor degree in Biology. He earned his Master of Public Policy degree from the Gerald R. Ford School of Public Policy at the University of Michigan in 2009. During Yiwei's PhD study, his dissertation focused on regulations and their impacts on the automobile industry and vehicle usage in U.S. households. He is proficient in using programs and statistic packages, including STATA, SAS, Matlab, and R. He also has rich experience in working on large household datasets, such as the National Household Travel Survey (NHTS) data. In addition to his research, Yiwei had also worked as a teaching assistant for nine semesters in four different courses, including Behavioral Economics, Environmental Economics, Strategic Pricing, Introduction to Business Regulation for business majored students at the Dyson School.

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CHAPTER 1

INTRODUCTION

One of the most important roles of government is to intervene when certain social, environmental goals or public goods are necessary but cannot be achieved within a free market. Regulations are often used in these cases and sometimes they produce unintended outcomes. Some of these unintended outcomes are positive and some are negative. Long run impacts, especially when technology advances rapidly, could be very hard for policy makers to anticipate when regulations were first designed. To better plan future regulations, it is important to study the results of past and exiting regulations to understand their full impacts on the society. Assessments of these impacts are key to a successful cost and benefit analysis. In my dissertation, I focused on CAFE standards and their impacts in the United States, some of which were not fully realized when CAFE standards were first introduced.

CAFE standards were enacted by the Congress in 1975. At that time, global warming was not such a hot topic as it is today. The main reason of adopting CAFE standards was to reduce U.S.'s dependence on foreign oil amid the oil crisis in the 1970s. It was seen more as a national security issue rather than an environmental issue. The majority of the U.S. public preferred vehicles with large internal spaces and great horse power. In the early 1970s, the average fuel economy of cars was only in the vicinity of 11-12 miles per gallon (MPG). Fuel economy was not systematically tested and in publications that introduce vehicle models, such as the Ward's Automotive Yearbooks, fuel economy was not even listed among vehicle model attributes. There were several efficient car models on the market, such as the infamous Ford Pinto, but the majority of the consumers did not care much for fuel economy. CAFE standards intervened this market by setting MPG standards for both cars and light duty trucks. The National Highway Traffic Safety Administration (NHTSA) regulates CAFE standards and the U.S. Environmental Protection Agency (EPA) is responsible for testing the fuel economy of new vehicle models. Each automobile company must have their sales weighted average fuel economy of all their products, under various brand names, meet the standards in each model year. CAFE standards apply to all domestic and foreign automobile companies that sell products on the U.S. market. A $55[1] fine is charged for each MPG per sold vehicle that fall below the standards.

CAFE standards started at 18 MPG for cars in model year 1978 and separate standards were set for two wheel drive and four wheel drive trucks in model year 1979, which were later replaced by a combined truck standard. The standards were much higher than the average fuel economy of vehicles sold in the early 1970s. As a result, automobile companies had to downsize their products, which means lowering weight, or lowering engine power, or doing both, to gain better fuel economy so that they can meet the standards within a short period of time. However, with so many older cars that weigh

[1] The fine was raised to $140 starting from model year 2015.

over 4,000 lbs. on the road, these new lighter vehicles raised concerns about safety. Researches showed that in two vehicle collisions, the greater the difference in vehicle weight, the larger chance that the passengers in the lighter vehicle get seriously wounded or even getting killed. In the long run, automobile companies had the option of increasing the efficiency of their products through technological innovation. The Obama Administration pushed for more aggressive CAFE standards as a measure to further cut greenhouse gas (GHG) emission in the transportation sector. However, given what automakers did when CAFE standards were first enacted, the public worried that the new stringent standards would trigger another wave of downsizing, which might have negative effect on road safety. In chapter two and three, I looked into the historical innovation rate under CAFE standards and decomposed innovation rate into natural innovation rate and induced innovation rate, which is stimulated by the tightening of CAFE standards. There are previous literatures that looked into the effect of regulations on innovation. I moved one more step forward and estimated the rate of response of technological innovation with respect to the rate of increases in the stringency of CAFE standards. I then predicted future innovation rate of automobile companies under the upcoming standards using these estimates to examine how much downsizing would happen.

The automobile companies have been regulated by CAFE standards, so it is not surprising that their behaviors were deeply influenced. However, CAFE standards also have profound effects in other areas. In the United States, the major source of road maintenance fund is the gasoline tax revenue. CAFE standards did a great job in making vehicles more efficient and thus reduced total gasoline consumption across the country.

As a result, gasoline tax revenue had been declining while the road maintenance expenditure kept increasing. While expenditure are going up, partly because of inflation, it remains extremely hard for the government to raise the gasoline tax. Any idea of making major increases in gasoline tax rates would face great pressure from voters in the United States. Politicians have been reluctant to touch this issue and would rather seek other methods to solve this matter. Take the federal government as an example, the current federal gasoline tax rate is 18.4 cents per gallon, which was enacted in 1997. Despite all the discussions of global warming and emission cuts, the federal gasoline tax rate have not been raised for 19 years and there is still no sign that it would be raised any time soon. Local governments have also been facing this difficulty. With more aggressive CAFE standards on the way, the erosion in the gasoline tax revenue would only get worse in the future.

Mileage based tax, or a VMT tax was proposed as a replacement for the per gallon based gasoline tax in order to provide a more stable revenue for road maintenance. Dozens of pilot VMT tax projects were run across the country to study the feasibility of this tax and the State of Oregon went further to establish the first VMT tax program in 2015. In all these programs, global position system (GPS) devices were installed to track travel information so that usage fees could be charged accordingly. There have also been criticisms about the VMT tax. Some people had privacy concerns about having a GPS installed in their vehicle and report to the government of all their travelling behaviors. Some questioned the negative incentive a VMT tax would place on purchasing and using of highly efficient vehicles, such as hybrid vehicles and electric vehicles. These vehicles, designed with new technologies, allow their users to pay little or even no fees under the current gasoline tax. Other challenges include the jurisdictional barriers in tax distribution and the high costs in collecting VMT tax, mainly because of the installation of extra equipment, and the high transition costs when VMT taxes and gasoline taxes co-exit. Obama decided to not to pursue a VMT tax during his term of office. However, as the overall fleet fuel economy kept increasing, the government will have to face the hard choices between making major increases in gasoline taxes and reforming of taxation.

In chapter four and five, I used the 2009 National Household Transportation Survey data to explore the driving behavior in households nationwide. I estimated the annual VMT in households with respect to the cost changes in fuel while taking into account the different types of vehicles households possessed. I then simulated the changes in driving mileage as well as the tax revenue under different scenarios to compare the gasoline tax and the VMT tax.

CHAPTER 2

AUTOMOBILE INNOVATION AND CAFE STANDARDS IN THE US

Introduction

According to the EPA estimates, the United States produces around 6,000 million metric tons of energy-related CO_2 emissions every year. As one of the major GHG emitters, emission cuts in the United States could have a large impact on the global environment. Light duty vehicles, including passenger cars and light duty trucks, are one of the major sources of GHG emissions and contribute approximately 20 percent of the total energy-related GHG emissions in the United States. Not surprisingly, various policies have been introduced to reduce emissions and energy consumption in this sector. CAFE standards were first enacted in 1975 by the congress. The standards target on the sales weighted average[2] fuel economy, measured in MPG, of automobiles from all automakers that run businesses in the United States. CAFE standards were first introduced to passenger cars in model year 1978 and to light duty trucks in model year 1979. Though CAFE standards were initially enacted as a response

[2] The EPA uses harmonic mean instead of arithmetic mean in calculating CAFE.

to the oil crisis in the early 1970s, it is now used as one of the most important regulations to control GHG emissions in the United States.

There are several ways for automakers to meet CAFE standards. Empirical studies in engineering show that automakers can sacrifice engine power and vehicle weight to get higher fuel economy[3] without applying new technologies. That was exactly what firms did when CAFE standards first came into effect. As a result, the vehicle attributes changed rapidly in the late 1970s and early 1980s. Down-weighting and lowering engine power are not the only ways firms can improve fuel economy. Innovation also allows firms to produce more efficient products without sacrificing vehicle performance, which consumers care about the most. Firms can improve the thermodynamic efficiency of their engines, lower frictions that include rolling resistance and frictions within the mechanical system, and improve aerodynamic designs to gain better fuel economy. However, new innovation in these areas needs investment in R&D and could take many years to improve and become commercially profitable.

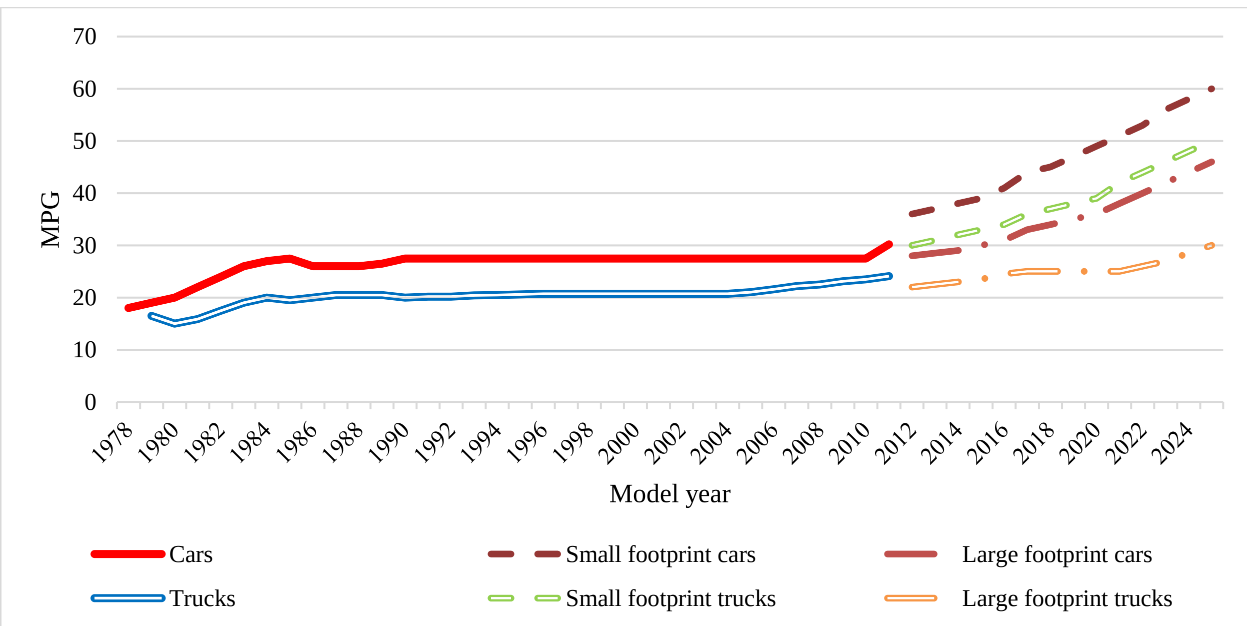
Previous studies in regulation and innovation show that performance standards are capable of inspiring innovation in many industries. In this chapter, I analyze vehicle attribute data to answer two related questions. First, how was innovation affected by the changes in CAFE standards in the automobile industry in the United States? Second, what would happen to innovation under the new standards? I focused on investigating the relationship between the rate of innovation related to fuel economy and the changes

[3] The energy needed to travel a certain distance (fuel efficiency) is proportionate to the work performed by the engine, which is a product of force and distance traveled, $dW=F*dS$. To lower F to get better fuel efficiency, one way for firms to accomplish this quickly is to reduce vehicle weight, so that friction between road and wheels could be lowered and, thus, less force is needed to move the vehicle. Another fast approach is to lower engine power, which would sacrifice acceleration performance of vehicles. Firms can also do both.

in CAFE standards. I used a broad definition of innovation in this paper. Following Joseph Schumpeter (1942), I considered all successful commercial applications of invention, new ideas and designs, and adoption of ideas or technologies from diffusion, to be innovation.

As shown in Figure 2.1, the standard for passenger cars was set at 18 MPG for model year 1978, and it kept increasing over the next few years until it hit 27.5 in 1986. The 27.5 MPG standard for cars remained stable from 1990 to 2010[4]. Firms made dramatic down-weighting in their vehicles and used less powerful engines to meet the standards in the late 70s and early 80s. Later, when the standards were stable in the 90s,

Figure 2.1 CAFE standards over time (MPG).



Note: The truck standard from model year 1979-1981 is the mean of 2WD and 4WD standards. Starting from model year 1982 is the combined truck standard. CAFE standards are set based on footprint in model year 2012. The large cars/truck and small cars/truck standards show the lower and upper bound of the standards.

[3] The car standard was lowered to 26 in 1987 and raised back to 27.5 in 1990.

firms kept average MPG around the standard and produced heavier and more powerful vehicles with new innovations.

In 2011, President Obama announced new aggressive CAFE standards, which seek to almost double the overall fuel economy of passenger vehicles by 2025 compared with 2011. The goal was to attain an average MPG of 54.5 in 2025 model year vehicles, passenger cars and light duty trucks combined, which is much higher than the 27.4 MPG in 2011. With such an aggressive shift in CAFE standards, there is an ongoing discussion about whether auto makers would provide consumers with much lighter and less powerful products, which might further raise safety concerns, similar to what happened in the 1970s when CAFE standards first came into effect.

My work mainly differs from previous literature in two ways. First, while previous studies suggested that regulation can indeed speed up innovation, none of them were able to quantify the innovation rate with respect to the changes in the stringency of standards. I move one step forward and decompose innovation into two parts. One is the natural innovation, which occurs regardless of pushes from regulations. The second part is induced innovation, which is in direct response to the tightened standards. Therefore, I not only show that changes in regulations can impact innovation, but I also show that changes in the rate of innovation is proportional to changes in CAFE standards.

Second, by decomposing innovation and quantifying the response rate of induced innovation to the stringency of standards, I turn innovation rate into a function of regulation stringency. Using this method, I provide a better tool to predict future innovation under new regulations. Instead of picking a vague rate of innovation, such as a mean rate from previous data, I can now adjust the predicted innovation rate based on the change in the stringency of upcoming regulations.

My results suggest that automakers improved their technology over time at a natural innovation rate. To be more specific, in the car sector, the natural innovation in fuel economy related technologies could increase the fuel economy of cars by 1.19 percent annually, if vehicle weight and engine power were kept constant. Likewise, in the light truck sector, there was a natural innovation rate of 0.67 percent annually. When the stringency level of standards changed, automakers also adjusted their innovation rates in response to such changes. They were able to innovate faster compared to the natural rate when facing pressure from tightened standards. Every one percent increase in CAFE standards induced an additional 0.32 percent improvement in total innovation in cars. And in the truck sector, every one percent increase in CAFE standards induced an additional 0.62 percent in fuel economy-related innovation.

Using these results, I predict that additional innovation induced by the more stringent new standards would play an important role under the new aggressive standards. In the car sector, average fuel economy would increase by 41 percent, if weight and engine power were kept at 2011 levels. However, such improvements would still not be fast enough to meet the 2025 target, so firms will have to downsize their products to gain higher MPG. I estimate that cars will have to be downsized[5] to the late 90s' level to be able to comply with the 2025 standards. In the light truck sector, average fuel economy would increase by 45 percent, if weight and engine power

[5] Downsizing of vehicles means lowering weight or engine power or both. Firms typically do both when they lower engine power to reduce the negative impact on vehicle performance, such as acceleration.

remained at 2011 levels. Because the standard increase is relatively smaller in the truck sector compared to that of the car sector, I estimate that firms will only have to downsize their product to the late 2000s' level to meet the 2025 target. The method I use in this chapter can also be applied to other industries where there are performance standards whose level of stringency changes over time and have a direct impact on innovation.

Literature Review

There is a rich body of literature about the relationship between regulation and innovation. The effect of regulation on innovation varies among different industries and among different regulation types. For example, Grabowski and Vernon (1977) found that more stringent screening of new drugs would decrease innovation of new drugs in the pharmaceutical industry. Thomas (1990) showed that small pharmaceuticals are more sensitive to increases in stringency, but large firms are less affected. In the energy sector, Popp (2006) found that more stringent U.S. emission standards increased domestic innovation in electric utilities. Johnstone et al. (2008) examined various economic regulations on renewable energy in OECD countries, and the results varied across different types of energy sources. In the automobile sector, most evidence showed positive effects of regulation on innovation. Atkinson and Garner (1987) found positive impacts on innovation from the introduction of stringent emission standards in 1970, CAFE standards in 1975[6], and the stringent safety standards in 1967.

[6] CAFE standards were enacted by Congress in 1975 and took effect in model year 1978.

Although patent data are used widely as a measure of knowledge stock in studying innovation, product attributes can also be used as an index of innovation. Newell, Jaffe, and Stavins (1999) built "characteristics transformation surface" using attributes of air-conditioners to study the relation between technology growth and trade-offs between energy usage and performance in energy-consuming products. They found that energy efficiency, directed innovation responded substantially after the initiation of energy-efficient product labeling, such as energy star, was required. To apply the idea of "characteristics transformation surface" to other products, it is important that the attributes of the product are indeed transferable to each other. Empirical studies of automobiles support such a relationship among vehicle weight, fuel economy, and engine power. For example, Murrell (1999) estimated that each percent increase in 0–60 MPH time (i.e., slower acceleration performance[7]) implied a 0.44 percent improvement in a fleet's average fuel economy.

Following the same idea of "characteristics transformation surface" in Newell, Jaffe, and Stavins (1999), Knittel (2011) studied the trade-off between light duty vehicle attributes including MPG, weight, and engine power under the pressure of CAFE standards. He then estimated the rate of shift of this surface over time and, thus, estimated the rate of innovation over time. He predicted that if weight, horsepower, and torque were fixed at their 1980 levels, MPG could have risen by 60 percent from 1980 to 2006. Also, to meet with Obama's aggressive CAFE standards will require major downsizing of vehicles. Using the same framework, Klier and Linn (2013) reported that

[7] Acceleration rate is a function of vehicle weight, and torque, which is one measure of the power of an engine.

increases in CAFE standards in the truck sector had a positive impact on innovation. These empirical results are supportive of using vehicle attributes to model innovation.

An enormous amount of work has been done studying the effects of CAFE standards. Other than Knittel (2011) and Klier et al. (2013) mentioned above, Goldberg (1998) showed that firms would have produced cars with lower MPG had the CAFE standards not been in place. Because firms were taking corner solutions in their MPG choice when CAFE standards were effective and binding, there was no incentive for firms to develop vehicles with better MPG. Instead, firms produced more small cars and less large cars to make sure the average MPG met the standards. This could be the explanation of the almost flat average MPG after 1983, when CAFE standards remained stable. Lutsey and Sperling (2005) also pointed out that vehicles became heavier and more powerful when the CAFE standards stopped increasing and, as a result, MPG remained unimproved. They treated the increase in weight and power while MPG remained stable as evidence of technological improvements that were directed to personal interests instead of pubic interests, such as fuel economy.

Whether CAFE standards made vehicles unsafe is also a viable topic. Greene (1998) concluded that CAFE standards had achieved their goal at a small cost. He argued that the previous concerns about safety, rebound effect, and consumer surplus were either minor or had not materialized. However, he also agreed that although the standards could be raised further, the regulator must give automakers enough time to adjust and improve their technologies to mitigate potential cost. Ahmad and Greene (2005) focused on the highway fatality rate from 1966 to 2002 and average fuel economy of vehicles during the same period. Their results suggested a negative relationship between average fuel economy and the fatality rate from automobile accidents. They argued that such a relationship does not support the assertion that CAFE standards were making driving less safe.

Scholars also predicted future vehicle attributes under CAFE standards. Besides Knittel (2011), DeCicco and Ross (2001) estimated that by 2010-2015, there could be a 47 percent increase in overall MPG from 24 to 35 with a reduction in curb weight of 14 percent compared to the 2000 level.

The overall MPG could even reach 44 with a reduction in curb weight of 26 percent compared with the 2000 level. Such predictions are important for policy makers in designing future CAFE standards, as they provide more information of potential social costs.

Theoretical and empirical models

In this part of the research, my focus is on the relationship between innovation and changes in CAFE standards. Following Knittel's (2011) vehicle attribute surface framework, I modelled innovation under CAFE standards as follows. Firms choose the attributes of their products, including engine power (hp_{it}), torque (tq_{it}), curb weight (w_{it}), fuel economy (mpg_{it}), other attributes that are related to fuel economy (X_{it}), and attributes related to other aspects (Y_{it}), at time t given the profitable technologies available at time t. I represent it as:

(1) $K_{it}=f(mpg_{it}, w_{it}, hp_{it}, tq_{it}, X_{it}, Y_{it}, t)$

The purpose of this study was to estimate innovation that was related to fuel economy, which included innovation that affects fuel economy directly, and innovation that affected other vehicle attributes that are transferable to fuel economy, such as weight and engine power. I assumed that K was additively separable in attributes related to fuel economy and in attributes that were not related to fuel economy, that is

(2) $K_{it}=U_t(mpg_{it}, w_{it}, hp_{it}, tq_{it}, X_{it})+D(Y_{it}, t)$,

where U is the level of profitable technologies that are related to fuel economy available at time t, and D is the level of technologies that are unrelated to fuel economy, such as safety, available at time t. My focus is on the progress of the level of U over time and the level set of U can be expressed as

(3) $MPG_{it}=g(W_{it}, HP_{it}, TQ_{it}, X_{it}|U_t)$

Following Knittel (2011), I assume the Cobb-Douglas functional form in U. Then the fuel economy is modeled as

(4) $\ln MPG_{it}= \beta_1 \ln W_{it}+\beta_2 \ln HP_{it}+ \beta_3 \ln TQ_{it} +\beta_4 M_t + \beta_5 M_t*t +X'_{it}B+e_{it}$,

where M is the dummy of having a manual transmission, X includes a set of dummies of fuel type and a turbo-charged engine, which could also affect performance of fuel economy.

After building the level set of U, the next step is to model the change in the level of U over time. I model the level of U at year t with respect to year t-1 as

(5) $U_t/U_{t-1}=(S_t/S_{t-1})^m EXP(j+\varepsilon_t)$,

where S is the fuel economy standard, m is the innovation rate that is induced by standard changes, j is the average annual innovation rate, and ε is a normally distributed, zero mean error term, which represents fluctuation in the annual innovation under natural growth. I assumed independency of ε in different model years. Then, in each model year after CAFE was enacted, I have

$$(6) \qquad U_t/U_0=(S_t/S_0)^m EXP(t*j+\sum\varepsilon_t)$$

Finally, I have my empirical model of innovation that is related to fuel economy as

$$(7) \qquad lnMpg_{it}= \beta_1 lnW_{it}+\beta_2 lnHP_{it}+ \beta_3 lnTQ_{it}+j*t+ m*lnSt+ \beta_4 M_t + \beta_5 M_t*t +X'_{it}B+e_{it}$$

Data

I tallied attributes of vehicle models that were sold in the U.S. market from Ward's Automotive Yearbook (WAY) from 1975 to 2011 and automobile-catalog.com (AC) from 1975 to 2011. Both datasets have their advantages and disadvantages. WAY covers a broader range of vehicles among 68 different makes. However, WAY does not provide complete information on torque in cars prior to 1997. Fuel type is also not reported directly in WAY. Therefore, I constructed the fuel type of internal combustion engine vehicles from the compression ratio reported in WAY. I assigned fuel type as gasoline if the compression ratio of the engine was less than 12, and I assigned fuel type as diesel if the compression ratio was above 12[8]. I also constructed the transmission type for earlier years in WAY[9], when several transmissions were reported for the same trim[10]. I chose only the first recorded transmission as the standard transmission to determine whether the trim was transmitted manually or automatically.

In the WAY data, the MPG reported were the EPA-adjusted MPG ratings. The EPA changed their method for estimating MPG ratings over time. Also, only the combined adjusted MPG rating was reported before 1985. Starting in 1985, adjusted MPGs were reported in two separate numbers, city MPG and highway MPG. The city MPG was calculated as 0.9*[EPA tested city MPG] and highway MPG was calculated as 0.78*[EPA tested highway MPG].

In 2008, the EPA adjusted their MPG rating method again. The new method took more variables, such as outdoor temperature and air-conditioning, into account. This change resulted in a decrease in EPA-adjusted MPG in most vehicles. The new formulas are shown as below

$$\text{Adjusted city MPG} = \frac{1}{0.003259 + \frac{1.1805}{\text{Tested city MPG}}}$$

$$\text{Adjusted highway MPG} = \frac{1}{0.001376 + \frac{1.3466}{\text{Tested highway MPG}}}$$

[8] Diesel engines require a high compression ratio to trigger combustion.

[9] More recent data report the standard transmission of the trim and list other transmissions that are available to consumers as options.

[10] Trims are more detailed settings within models. For example, 2011 Ford Taurus is a model, 2011 Ford Taurus SE and 2011 Ford Taurus SEL are different trims of the same model.

I used these formulas, provided by the EPA, and the adjusted MPG to reverse engineer and calculate the tested MPG and then I applied the formulas used prior to 2008 to get adjusted MPG numbers that were comparable to those of previous model years. I then applied the same method that the EPA used to construct the combined MPG, which was the weighted, harmonic mean of adjusted city MPG and adjusted highway MPG using a city/highway ratio of 0.55/0.45. I added a dummy into the regression specifications to control for the difference between combined fuel economy from the WAY data and from the AC data. I did this because MPG reported in the AC data was estimated by European engineers, and was not tested and calculated using EPA methods.

The AC data that I had permission to use covered 23 major makes, but provided more comprehensive information in vehicle MPG and torque. The AC data also provided full information about transmission types and fuel types for all trims. The MPG reported in the AC data were not EPA ratings, but estimates made by engineers.

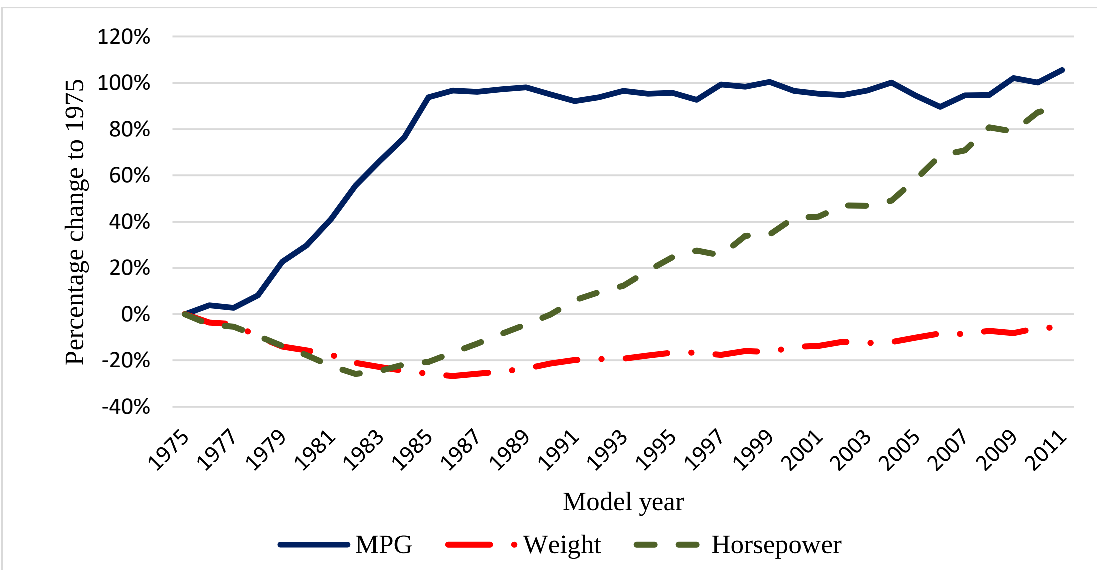
Vehicles that have a gross weight above 8500 lbs., typically heavy duty trucks, are not regulated by CAFE standards, therefore, I removed these vehicles from my analysis. I also removed from my analysis hybrid vehicles and electric vehicles that have MPGs above 70, because these vehicles use very different technologies; the empirical model for internal combustion engine vehicles might not be suitable for estimating innovation and for reflecting attribute tradeoffs in these vehicles.

Evidence of attribute tradeoffs and technological progress

The fuel economy of vehicle models changed dramatically after CAFE standards were enacted. Figure 2.1 shows the changes in CAFE standards over time. The standards went into effect in 1978 for cars and in 1979 for trucks. The standards increased sharply at the beginning and then remained stable in the 1990s and 2000s. The car standards remained stable until 2011, but the truck standards started to increase again after model year 2004. The Obama administration set aggressive new standards, and these new standards after the 2011 model year will be based on the footprints[11] of vehicles.

Figure 2.2 shows how the average weight, horsepower, and fuel economy changed from 1975 to 2011. Compared to passenger cars in model year 1975, average MPG almost doubled in 1986 and remained at stable until 2011. Average horsepower

Figure 2.2. Changes in main car attributes from 1975 to 2011.



Note: The mean MPG, horsepower and weight of all car models in model year 1975 were set as the baseline and I report the percentage changes of the means of these attributes.

decreased by over 20 percent in 1982 compared to 1975 models, and then horsepower kept increasing annually; in 2011 it was 90 percent higher than that of 1975 models.

[11] Footprint is calculated as vehicle width times length of wheelbase.

Similarly, average curb weight of cars decreased sharply during the period when CAFE standards were increasing. Average weight decreased by 25 percent from model year 1975 to 1986, and then increased gradually and almost returned to the 1975 level in 2011.

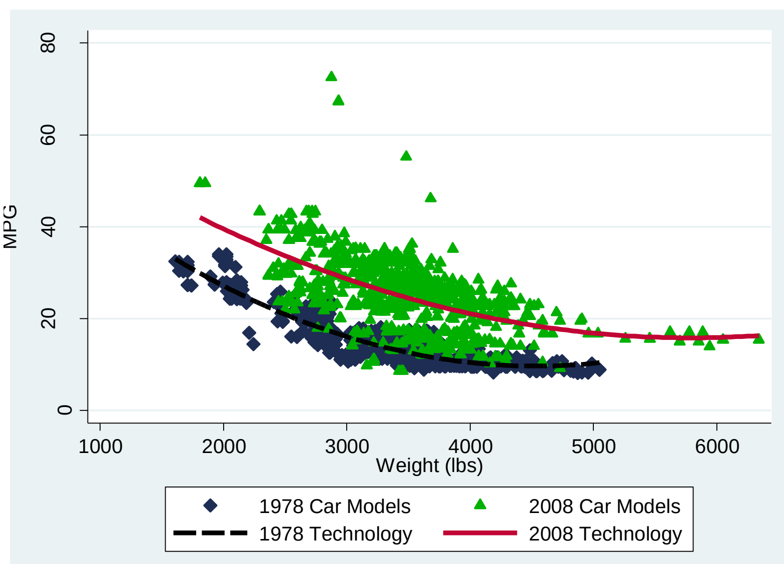
I observed a similar trend in the light duty truck sector, where CAFE standards were first introduced at 17.2 MPG for two-wheel drive (2WD) trucks and 15.8 MPG for four-wheel drive (4WD) trucks. The separate standards for 2WD trucks and 4WD trucks were disconnected after 1992. A combined standard was introduced later in 1982 at 17.5 MPG and all standards kept increasing till 1987[12], when the combined standard was at 20.5 MPG. The combined standard approximated 20.5 for a few years and remained stable at 20.7 MPG from 1996 to 2004. The truck standards increased slowly again in 2005 and kept increasing to 24.1 in 2011. During the 1975-2011 model years, average weight of light trucks also dropped sharply in the early years when the standards came into effect, and then in 2011they increased to 20 percent higher than the 1975 level. Average horsepower decreased slightly at the beginning and then increased to 110 percent higher than the 1975 level during the same period.

These data show that, first, when standards increased faster than the innovation rate in the industry, firms were capable of lowering the weight and horsepower of their products to gain better fuel economy. The changes in average weight, horsepower, and MPG during the late 70s and early 80s reflected such behavior, and these changes were consistent with empirical findings in engineering that weight, engine power, and fuel

[12] Firms were allowed to choose to comply with the combined truck standard or the separate standards for 2WD and 4WD trucks from 1982 to 1992. Most firms chose to comply with the combined standards.

economy are transferable to each other. Second, as technologies advance over time, firms are capable of building vehicles that are better in every dimension. The changes in average horsepower and weight during the period when CAFE standards were stable show that innovation over time allows firms to build vehicles with similar MPG, but are much more powerful and heavier. Because horsepower and weight can be transferred to MPG, such changes suggest that firms should be able to build vehicles that are more fuel-efficient over time if they keep weight and engine power stable. Not surprisingly, firms were able to produce cars that were heavier and more efficient in 2008 compared to 1978 (Fig. 2.3). Such a shift in the plotting of attributes can be seen also in engine power and fuel economy, and this is clear evidence of innovation.

Figure 2.3 Technological innovation of cars from 1978 to 2008.



Note: The technology level is the quadratic fitted line of vehicle weight and MPG of the corresponding model year.

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CHAPTER 3

THE IMPACT OF CAFE STANDARDS ON INNOVATION

Introduction

In this chapter, I present the regression results of the model discussed in chapter two and discuss the intuition behind these results. I then predict future technology progress under the new aggressive CAFE standards using my findings.

Empirical results

Tables 3.1 and 3.2 report the regression results of passenger cars and tables 3.3 and 3.4 report the regression results of light duty trucks. Tables 3.1 and 3.3 also provide comparisons between firms from different origins, and tables 3.2 and 3.4 compare among different vehicle classes.

Trade-offs among vehicle attributes

Coefficients of engine power, which is measured by torque, horsepower, and weight suggest that they are correlated negatively to fuel economy. This is consistent with empirical studies in engineering, which emphasize that weight or engine power can be lowered to gain higher MPG. Vehicles using diesel engines usually have better fuel economy compared to vehicles using gasoline engines due to the higher efficiency of

Table 3.1. Innovation response to CAFE standards in cars (1978-2011).

	All	US	Asian	EU
Log horsepower	-0.1378	0.0492	-0.4781***	-0.6089
	(0.0732)	(0.0389)	(0.1063)	(0.0977)
Log curb weight	-0.3770***	-0.2848***	-0.3061***	-0.3802***
	(0.0355)	(0.0331)	(0.0728)	(0.0423)
Log torque	-0.3533***	-0.5881***	-0.0245	0.2657***
	(0.0841)	(0.0388)	(0.1320)	(0.1072)
Manual	0.1341***	0.1157***	0.0954***	0.1142***
	(0.0186)	(0.0214)	(0.0196)	(0.0543)
Manual*trend	-0.0067***	-0.0051***	-0.0047***	-0.0043***
	(0.0007)	(0.0007)	(0.0010)	(0.0021)
Diesel fuel	0.1637***	0.1340***	0.1999***	0.1362***
	(0.0537)	(0.0185)	(0.0814)	(0.0298)
Turbocharged	0.1430***	0.1405***	0.1235***	0.0213***
	(0.0161)	(0.0250)	(0.0201)	(0.0227)
Wards	0.3977***	0.4147***	0.3360***	0.4147***
	(0.0141)	(0.0115)	(0.0210)	(0.0234)
Log CAFE standards	0.3205***	0.3089***	0.4225***	-0.2012
	(0.0353)	(0.0388)	(0.0799)	(0.1366)
Yearly trend	0.0119***	0.0079***	0.0130***	0.0129***
	(0.0013)	(0.0005)	(0.0006)	(0.0011)
Firm fixed effect	Y	Y	Y	Y
R-squared	0.8971	0.9181	0.8553	0.7637
Obs	21,656	12,870	5,501	3,066

Note: The dependent variable is log MPG. I compared the results among automakers with different countries of origins.

diesel engines. Another important factor that affects fuel economy is the type of transmission. Manually-transmitted vehicles are normally more fuel efficient than automatically-transmitted vehicles of the same model. However, the coefficients of the interaction terms of manual transmission and the time trend show that the difference had been decreasing over time for both cars and trucks. In fact, vehicles with some of the

Table 3.2. Comparison of innovation responses among car classes.

	Small cars	Medium Cars	Large cars	Economy cars	Luxury cars
Log horsepower	-0.2300***	-0.1275***	0.0722	-0.0867	-0.2597***
	(0.0948)	(0.0547)	(0.0561)	(0.0651)	(0.1269)
Log curb weight	-0.2994***	-0.4589***	-0.4882***	-0.3788***	-0.2921***
	(0.0563)	(0.0713)	(0.0926)	(0.0460)	(0.0565)
Log torque	-0.2808***	-0.3734***	-0.4676***	-0.4253***	-0.1954
	(0.1162)	(0.0519)	(0.0859)	(0.0650)	(0.1299)
Manual	0.1389***	0.1014***	0.0385	0.1300***	0.0831***
	(0.0132)	(0.0390)	(0.0178)	(0.0157)	(0.0445)
Manual*trend	-0.0061***	-0.0049***	-0.0001***	-0.0063***	-0.0040***
	(0.0006)	(0.0016)	(0.0008)	(0.0005)	(0.0017)
Diesel fuel	0.2490***	0.0735	0.2197***	0.2118***	0.0566
	(0.0523)	(0.0474)	(0.0185)	(0.0688)	(0.0679)
Turbocharged	0.1271***	0.1916***	0.2609***	0.0895***	0.1331***
	(0.0155)	(0.0182)	(0.0211)	(0.0237)	(0.0348)
Wards	0.3543***	0.4041***	0.5065***	0.3538***	0.4833***
	(0.0171)	(0.0131)	(0.0104)	(0.0133)	(0.0253)
Log CAFE standards	0.3456***	0.3058***	0.3101***	0.2695***	0.4373***
	(0.0575)	(0.0594)	(0.1496)	(0.0382)	(0.1246)
Yearly trend	0.0129***	0.0117***	0.0052***	0.0123***	0.0101***
	(0.0012)	(0.0012)	(0.0020)	(0.0012)	(0.0026)
Firm fixed effect	Y	Y	Y	Y	Y
R-squared	0.8609	0.8901	0.9336	0.9325	0.7971
Obs	10185	8525	2946	16287	5369

Note: The dependent variable is log MPG. I compared results among car classes following definitions in Ward's Automotive Yearbook.

modern automatic transmissions, such as the Continuously Variable Transmission (CVT), have similar or even better performance in fuel efficiency compared to vehicles with manual transmissions.

Table 3.3. Innovation responses to CAFE standards in trucks (1979-2011).

	All	US	Asian	EU
Log horsepower	0.0589	0.0927	0.0253	-0.0946
	(0.0431)	(0.0711)	(0.0716)	(0.0894)
Log curb weight	-0.3975***	-0.3797***	-0.4283***	-0.5554***
	(0.0295)	(0.0507)	(0.0412)	(0.0737)
Log torque	-0.4318***	-0.4788***	-0.3781***	-0.1819
	(0.0642)	(0.1050)	(0.0761)	(0.1146)
Manual	0.0783***	0.0855***	-0.0439***	-0.0174***
	(0.0133)	(0.0191)	(0.0415)	(0.0433)
Manual*trend	-0.0043***	-0.0045***	-0.0002***	-0.0001
	(0.0007)	(0.0012)	(0.0018)	(0.0013)
Diesel fuel	0.3468***	0.3452***	0.4524***	0.3051***
	(0.0695)	(0.0991)	(0.0213)	(0.0540)
Turbocharged	0.1043***		0.0648***	0.0743***
	(0.0182)		(0.0141)	(0.0277)
Wards	0.4070***	0.4259***	0.3390***	0.3699***
	(0.0136)	(0.0161)	(0.0198)	(0.0339)
Log CAFE standards	0.6239***	0.6306***	0.4530***	1.1270***
	(0.1966)	(0.3151)	(0.1492)	(0.3600)
Yearly trend	0.0066***	0.0056***	0.0086***	0.0046
	(0.0015)	(0.0022)	(0.0030)	(0.0068)
Firm fixed effect	Y	Y	Y	Y
R-squared	0.865	0.8612	0.8145	0.9191
Obs	14724	10369	3775	566

Note: The dependent variable is log MPG. I compared the results among automakers with different countries of origins.

Table 3.4. Comparison in innovations among truck classes.

	Pickups	CUV/SUV	Vans
Log horsepower	-0.0270	0.0818	0.0498
	(0.0241)	(0.0853)	(0.0413)
Log curb weight	-0.2808***	-0.4397***	-0.7404***
	(0.0195)	(0.0244)	(0.0403)
Log torque	-0.2736***	-0.4617***	-0.2448***
	(0.0358)	(0.0843)	(0.0232)
Manual	0.0492	0.0939	0.2152
	(0.0275)	(0.0117)	(0.0358)
Manual*trend	-0.0027***	-0.0040***	-0.0084***
	(0.0013)	(0.0009)	(0.0021)
Diesel fuel	0.3086***	0.3818***	
	(0.0238)	(0.0790)	
Turbocharged	0.0259***	0.1341***	
	(0.0086)	(0.0145)	
wards	0.3768***	0.4129***	0.3337***
	(0.0235)	(0.0163)	(0.0203)
Log CAFE standards	0.8959***	0.4719***	0.3913***
	(0.0448)	(0.1726)	(0.1257)
Yearly trend	0.0009	0.0088***	0.0065***
	(0.0022)	(0.0008)	(0.0018)
Firm fixed effect	Y	Y	Y
R-squared	0.7782	0.8904	0.8145
Obs	4267	8748	3775

Note: The dependent variable is log MPG. I compared results among truck classes following definitions in Ward's Automotive Yearbook.

Natural rate of innovation

The coefficients of year trend estimate the average annual growth rate of fuel economy related technologies. My results suggested that on average, firms had an annual innovation of 1.19 percent in the fuel economy of their passenger cars. Note that this is not saying the actual fuel economy of new car models increased every year. The interpretation is that the natural innovation allowed firms to increase the fuel economy by 1.19 percent, assuming that other vehicle attributes, including engine power and weight, were kept constant. Firms could also increase weight or engine power instead of fuel economy to make their product more attractive to their customers. That is exactly what they did when CAFE standards were stable. Similarly, in the light duty truck sector, the natural innovation rate was 0.66 percent annually. These estimates are the average innovation rate for all firms. As shown in tables 3.1 to 3.4, innovation rate varied across firms from different countries and different vehicle classes. For example, while the U.S. automakers had annual innovation rates at 0.79 percent in cars and 0.56 percent in trucks, Asian automakers had annual innovation rates at 1.3 percent in cars and 0.86 percent in trucks. Also, small cars appeared to enjoy a higher innovation rate than large cars, and SUV/CUVs led in innovation rate among trucks.

Innovation in response to CAFE standards

Induced innovation is the key focus of this paper. My results showed that in both the passenger car and light truck markets, the changes in the level of CAFE standards had a significant effect on the fuel economy-related innovation in addition to the natural innovation rate. Also, the truck sector responded more strongly than the car sector.

The coefficients of the log of CAFE standards estimate the average induced innovation with respect to changes in CAFE standards. The estimates suggested that on average, a one percent increase in CAFE standards was associated with an additional 0.32 percent point increase in the innovation of fuel economy-related technologies of cars. Likewise, a one percent increase in CAFE standards was associated with an additional 0.62 percent point increase in the innovation for trucks. There are two explanations for the different responses for cars and trucks to the changes in CAFE standards. The first is that light duty trucks started at a relatively low technology level. When CAFE standards first came into effect, the market share of light duty trucks was merely 20 percent of the passenger vehicle market and there were very few international brands on the U.S. market. The market for cars, however, was much more mature and competitive. The second reason is that, as discussed in part B, the natural innovation rate of trucks was lower than that for cars. Therefore, being a relatively young product with low natural innovation, light duty trucks had more room for improvement when pushed by the increased standards.

I also broke down the data into various subgroups to explore the heterogeneity among different automakers and vehicle classes. As shown in table 3.1, in the passenger car market, both U.S. automakers and Asian automakers responded strongly to CAFE standards. This is surprising at first glance, because Asian makers had been producing cars with an average fuel economy that was well above CAFE standards. Small increases in CAFE standards should not have had a direct influence on the Asian makers. I explain this as evidence of market competition. U.S. automakers had been producing cars with an average fuel economy that barely met CAFE standards. Every time CAFE standards tightened up, U.S. automakers had to push harder in their innovation to increase their fuel economy to meet the higher standards. They were reluctant to simply lower weight and engine power, because these attributes were what consumers demanded in the United States. The traditional advantage of Asian cars had been fuel economy since the day they entered the U.S. market. To protect their advantages in the competitive market, Asian makers also had to increase fuel efficiency of their products when U.S. automakers improved theirs under the impetus of CAFE standards. Therefore, though most of the time the tightening in CAFE standards did not affect Asian automakers directly, the tougher standards still stimulated a faster innovation rate for Asian brand cars because of market competition.

There were also automakers that chose not to comply with CAFE standards and, instead, paid the fines. These were all European companies who specialized in producing luxury cars. Unlike U.S. and Asian automakers, European automakers did not show a significant response in innovation to the increases in CAFE standards. I explain this as the evidence that these European companies were able to pass down the fines to their consumers who cared more about the luxury features of their vehicles and who were less sensitive to prices. I did not observe such behavior in the luxury cars of U.S. and Asian automakers. There are two explanations for this. First, even though they were all luxury vehicles, U.S. and Asian luxury cars were usually less expensive than European luxury cars, which suggests that consumers who chose to purchase European luxury cars were probably richer and less price-sensitive than those who chose U.S. or Asian luxury cars. Second, U.S. and Asian automakers pushed their innovation in response to the increases in CAFE standards to either avoid paying fines or to maintain a market advantage. Most of these innovations could have been applied to both economy cars and luxury cars without extra costs. As a result, even though consumers of luxury cars may have been less price-sensitive, U.S. and Asian automakers did not apply significantly different compliance strategies for their economy cars and luxury cars.

Robustness checks

In this section, I discuss the potential concerns with the robustness of the results, and I perform a series of robustness checks to show that the estimates of the main results are sound.

Correlation between vehicle attributes

The first concern of the empirical model I used is that vehicle attributes were correlated with each other. When automakers design their vehicles, the combinations of installed equipment are not random. For example, engine power is highly correlated with vehicle weight. Automakers typically install more powerful engines in heavier and larger vehicles. Therefore, horsepower and weight are clearly correlated with each other. Though the focus of this paper is not on the tradeoff between attributes, but on the innovation rate, I still wanted to ensure that such correlations among attributes would not bias the estimation of innovation responses. To address this concern, I used the translog functional form instead of the Cobb-Douglas functional form in the technology level U. By introducing interaction terms between key vehicle attributes, I tested whether my estimates of innovation responses were sensitive to such correlations. Tables 3.5 and 3.6 show the regression results using the translog functional form in specification III, and the main specification is shown in specification II.

Table 3.5. Comparison of Innovation response in cars among different specifications.

	Spec I	Spec II	Spec III
Log horsepower	-0.4122***	-0.1378***	-1.0728***
	(0.0165)	(0.0732)	(1.3998)
Log horsepower squared			-0.4933***
			(0.0875)
Log horsepower*Log weight			0.0195
			(0.1733)
Log horsepower*Log torque			1.0932***
			(0.1607)
Log curb weight	-0.5840***	-0.3770***	5.8616***
	-(0.0311)	-(0.0355)	(1.4723)
Log weight squared			-0.5143***
			(0.1320)
Log weight*Log torque			0.3847
			(0.2608)
Log torque		-0.3533***	-2.2422***
		(0.0841)	(1.8252)
Log torque squared			-0.6405***
			(0.1297)
Manual	0.1490***	0.1341***	0.1122***
	(0.0184)	(0.0186)	(0.0197)
Manual*trend	-0.0074***	-0.0067***	-0.0050***
	(0.0007)	(0.0007)	(0.0008)
Diesel fuel	0.1122***	0.1637***	0.2129***
	(0.0501)	(0.0537)	(0.0521)
Turbocharged	0.1235***	0.1430***	0.1232***
	(0.0268)	(0.0161)	(0.0186)
wards	0.3983***	0.3977***	0.3921***
	(0.0148)	(0.0141)	(0.0139)
Log CAFE standards	0.3792***	0.3205***	0.2243***
	(0.0289)	(0.0353)	(0.0353)
Yearly trend	0.0157***	0.0119***	0.0119***
	(0.0004)	(0.0013)	(0.0010)
Firm fixed effect	Y	Y	Y
R-squared	0.8883	0.8971	0.9036
Obs	21656	21656	21656

Note: The dependent variable is log MPG. Spec I and II use the Cobb-Douglas functional form of technology level and Spec I removes torque from regression. Spec III uses the translog functional form assumption.

Table 3.6. Comparison of Innovation response in trucks among different specifications.

	Spec I	Spec II	Spec III
Log horsepower	-0.2806***	0.0589	-0.0579
	(0.0215)	-(0.0431)	-(1.0173)
Log horsepower squared			-0.2200***
			(0.0959)
Log horsepower*Log weight			0.1241
			-(0.2097)
Log horsepower*Log torque			0.2585
			-(0.2780)
Log curb weight	-0.5980***	-0.3975***	2.8153***
	-(0.0184)	-(0.0295)	-(1.2335)
Log weight squared			-0.1609
			-(0.1096)
Log weight*Log torque			-0.2202
			-(0.2940)
Log torque		-0.4318***	-1.7171
		-(0.0642)	-(1.3189)
Log torque squared			0.1617
			-(0.2392)
Manual	0.0825***	0.0783***	0.0841***
	-(0.0226)	-(0.0133)	-(0.0110)
Manual*trend	-0.0049***	-0.0043***	-0.0047***
	-(0.0012)	-(0.0007)	-(0.0005)
Diesel fuel	0.2309***	0.3468***	0.3315***
	-(0.0594)	-(0.0695)	-(0.0608)
Turbocharged	0.0397***	0.1043***	0.0381
	-(0.0107)	-(0.0182)	-(0.0234)
wards	0.3982***	0.4070***	0.4061***
	-(0.0130)	-(0.0136)	-(0.0141)
Log CAFE standards	0.8299***	0.6239***	0.6115***
	-(0.1295)	-(0.1966)	-(0.2003)
Yearly trend	0.0107***	0.0066***	0.0064***
	-(0.0017)	-(0.0015)	-(0.0018)
Firm fixed effect	Y	Y	Y
R-squared	0.8385	0.865	0.8697
Obs	14726	14724	14724

Note: The dependent variable is log MPG. Spec I and II use the Cobb-Douglas functional form of technology level and Spec I removes torque from regression. Spec III uses the translog functional form assumption.

The annual innovation rate estimated using the translog model was almost identical to the estimates I obtained in the Cobb-Douglas model. The response rates of innovation to the changes in CAFE standards were also very close between the two specifications. Such results suggested that even though there are correlations among vehicle attributes, they did not appear to be a potential threat to the estimations of annual innovation rates and the response rates of innovation to standards.

Engine power measurement

The second concern I had was the measure of engine power. I used both highest torque and highest horsepower in the analysis. However, these two measures were also related closely. I show the specification keeping only horsepower in specification I and the estimates of natural innovation rate and response rate increased slightly compared to the main specification, which included both maximum torque and horsepower. The relationship between torque and horsepower is: Horsepower=Revolution per minute (rpm)*Torque/5252; and torque is a function of rpm. So, although these variables were highly correlated, keeping both maximum horsepower and maximum torque in the model still helped to control for more features of engine development over time. Therefore, I still chose the more conservative estimates in the main specification to predict future innovation.

Firm responses during different time periods

To predict automakers' future response to new CAFE standards, one important assumption I had to make is that firms would respond similarly to what they had done in the past. To test whether this was a reasonable assumption, I analyzed whether there were significant changes among firms' responses in the earlier years compared to more recent years. In the car fleet, CAFE standards were stable from 1990 to 2010 and only started to increase again in 2011. Therefore, I have little available information to make the comparison. In the truck fleet, however, CAFE standards were stable from 1996 to 2004, which allowed me to compare whether firms behaved differently prior to 1996 and after 2004. I compared the response rates in two different time windows for the truck fleet. The first response rate was from 1979 to 2004, which included the period when CAFE standards became effective and were being adjusted every year[13] (1979 to 1995), and the period when the standards were stable (1996 to 2004). The second window contained the stable period and the more recent period when CAFE standards started to increase again (2005 to 2011).

Table 3.7 reports the comparison between the two time windows and the results suggest that in both time windows, firms responded similarly to the changes in the standards. In the earlier period, the response rate was 0.727, and in the more recent years, the response rate was 0.604. The response rate was slightly higher in the earlier years, but the difference between the response rates during these two periods was not statistically significant. These results demonstrate that firms' response to changes in standards did not change dramatically during the past 30 years. Therefore, it is reasonable to assume that automakers would still be able to respond similarly to what they had done before. This supports the idea that it is reasonable to use previous innovation behavior as a reference in predicting future innovation.

[13] CAFE standards did not increase monotonically in the earlier years; for example, the standards for trucks were lowered in model year 1980, 1985, 1990, and 1992.

Table 3.7. Earlier year versus recent responses to CAFE standards in the truck sector.

	1979-2011	1979-2004	1996-2011
Log horsepower	0.0589	0.0043	-0.0187
	(0.0431)	(0.0436)	(0.0311)
Log curb weight	-0.3975***	-0.3985***	-0.4243***
	(0.0295)	(0.0518)	(0.0322)
Log torque	-0.4318***	-0.4043***	-0.3295***
	(0.0642)	(0.0869)	(0.0263)
Manual	0.0783***	0.1064***	0.0481
	(0.0133)	(0.0079)	(0.0503)
Manual*trend	-0.0043***	-0.0056***	-0.0033
	(0.0007)	(0.0006)	(0.0020)
Diesel fuel	0.3468***	0.2521***	0.3332***
	(0.0695)	(0.0582)	(0.0495)
Turbocharged	0.1043***	0.1591***	0.0822***
	(0.0182)	(0.0270)	(0.0134)
wards	0.4070***	0.3565***	0.4026***
	(0.0136)	(0.0232)	(0.0159)
Log CAFE standards	0.6239***	0.7269***	0.6042***
	(0.1966)	(0.1646)	(0.1450)
Yearly trend	0.0066***	0.0111***	0.0074***
	(0.0015)	(0.0020)	(0.0009)
Firm fixed effect	Y	Y	Y
R-squared	0.865	0.8854	0.8549
Obs	14724	7800	12025

Note: The dependent variable is log MPG. 1979-2011 represents the complete period of analysis of this paper. 1979-2004 includes the time when CAFE standards for trucks were actively increasing after it took effect and the period when the standards kept stable. 1996-2011 includes the period when the truck standards were stable and the period when truck standards started to increase again.

The role of gasoline prices

Vehicle usage are highly relevant to the cost of gasoline. Therefore, it is not surprising that one might expect a close relationship between the gasoline prices and the fuel economy related innovations. I incorporated the historical gasoline prices into the model to test whether fluctuations in gasoline prices have any effect on innovation.

Table 3.8. Role of real gasoline prices in vehicle innovation responses.

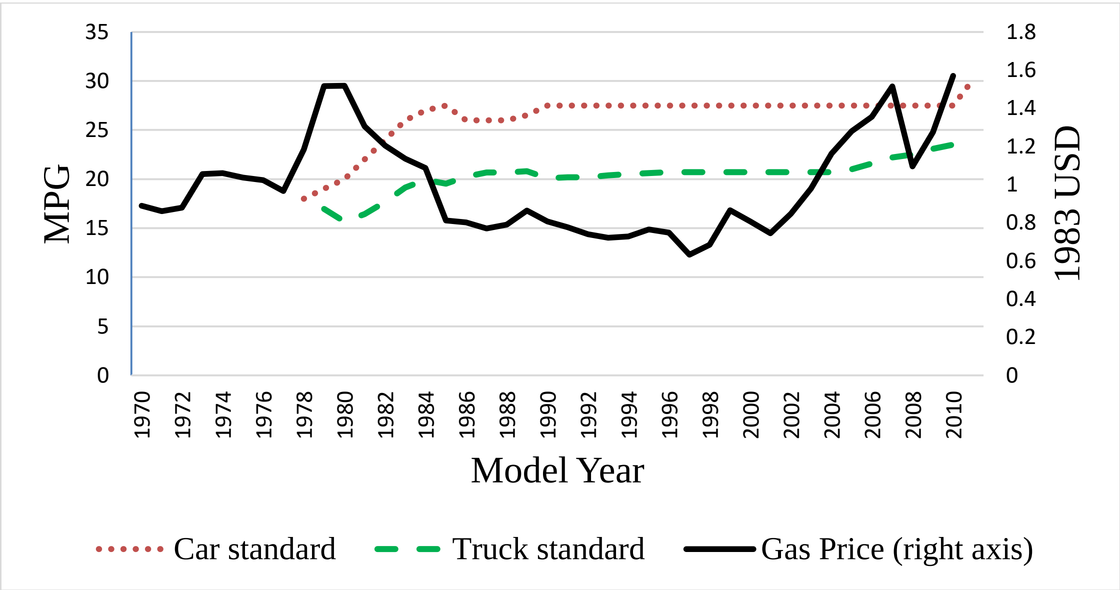
	Cars 1978-2011			Trucks 1979-2011		
	Spec II	Spec IV	Spec V	Spec II	Spec IV	Spec V
Log horsepower	-0.1378	-0.1441***	-0.1402	0.0589	0.0546	0.0534
	(0.0732)	(0.0725)	(0.0720)	(0.0431)	(0.0400)	(0.0391)
Log curb weight	-0.3770***	-0.3761***	-0.3769***	-0.3975***	-0.3893***	-0.3934***
	(0.0355)	(0.0360)	(0.0357)	(0.0295)	(0.0325)	(0.0328)
Log torque	-0.3533***	-0.3487***	-0.3515***	-0.4318***	-0.4318***	-0.4287***
	(0.0841)	(0.0841)	(0.0833)	(0.0642)	(0.0620)	(0.0611)
Manual	0.1341***	0.1338***	0.1340***	0.0783***	0.0870***	0.0837***
	(0.0186)	(0.0186)	(0.0186)	(0.0133)	(0.0117)	(0.0109)
Manual*trend	-0.0067***	-0.0066***	-0.0066***	-0.0043***	-0.0047***	-0.0046***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0006)	(0.0005)
Diesel fuel	0.1637***	0.1658***	0.1645***	0.3468***	0.3443***	0.3444***
	(0.0537)	(0.0524)	(0.0528)	(0.0695)	(0.0681)	(0.0671)
Turbocharged	0.1430***	0.1437***	0.1434***	0.1043***	0.1048***	0.1042***
	(0.0161)	(0.0164)	(0.0163)	(0.0182)	(0.0178)	(0.0181)
wards	0.3977***	0.3966***	0.3972***	0.4070***	0.4054***	0.4061***
	(0.0141)	(0.0142)	(0.0141)	(0.0136)	(0.0137)	(0.0139)
Log CAFE standards	0.3205***	0.3099***	0.3181***	0.6239***	0.6709***	0.6782***
	(0.0353)	(0.0295)	(0.0322)	(0.1966)	(0.1923)	(0.1668)
Gas price		-0.0174			-0.0292	
		(0.0167)			(0.0161)	
Lagged gas price			-0.0068			-0.0185
			(0.0187)			(0.0215)
Yearly trend	0.0119***	0.0121***	0.0119***	0.0066***	0.0069***	0.0066***
	(0.0013)	(0.0013)	(0.0013)	(0.0015)	(0.0015)	(0.0015)
Firm fixed effect	Y	Y	Y	Y	Y	Y
R-squared	0.8971	0.8973	0.8972	0.865	0.8656	0.8652
Obs	21656	21656	21656	14724	14724	14724

Note: The dependent variable is log MPG. All specifications use the Cobb-Douglas functional form of technology level and Spec IV and V include gasoline price into the regression. Spec IV uses the gasoline price one year ahead of model year, which is typically the year of introduction of the vehicles of those model years. Spec V uses gasoline price lagged for one year, which is two years ahead of model year.

As reported in Table 3.8, gasoline prices had no significant effect on fuel-economy related innovation. And the sign of the coefficient of gasoline price was negative, contrary to what one might expect. The reason that gasoline price did not affect innovation directly was that CAFE standards set the average fuel economy much higher than the undistorted market would have achieved. That is, even when gasoline prices were high, CAFE standards were still high enough to be binding. As a result, gasoline price fluctuations were not able to influence innovation directly.

The reason for having a negative coefficient for gasoline price lies in the way CAFE standards were announced. As shown in figure 3.1, CAFE standards were announced after the oil crisis in the 1970s. The target standards were announced years

Figure 3.1. Real gas price and CAFE standards



Note: Gasoline prices are normalized to 1983 dollars. The truck standard from model year 1979-1981 is the mean of 2WD and 4WD standards. Starting from model year 1982 is the combined truck standard.

ahead of being effective and they gradually increased in the first decade. However, during this period, when the standards were increasing and firms had a high rate of innovation, the real gas price dropped sharply and then stayed low for decades. As a result, when gas prices were included in the model, it only captured this negative correlation between the gas price and innovation. To conclude, with CAFE standards in place and being sufficiently high, gasoline price shocks had little direct effect on innovation in the automobile industry.

Future innovation prediction

In this section, I simulate innovation under the new standards using the estimated natural innovation rate and the induced innovation in response to CAFE standards. CAFE standards changed to footprint-based standards starting in 2012. Instead of a single average fuel economy standard for cars or trucks, the footprint-based method set different standards for vehicles based on their size. To simplify the simulation, I used the average change rates of the footprint-based standards in the simulation.

My calculations showed that the average fuel economy standard increased from 2011 to 2025 in cars by 72 percent, or a log increase of 0.542. I estimated the logarithm innovation rate compared to 2011 as

(8) $Growth_t = (T\text{-}2011) * j + (\log S_t - \log S_{2011}) * m$

where j is the average annual growth, T is the model year, S is CAFE standards, and m is the technological growth response to CAFE standards. In the car sector, as reported in section IV, j=0.0119 and m=0.32. Using (8) above and the estimates, I calculated that the total technological growth from the natural growth will be 0.167 in logarithm from 2011 to 2025 and the additional growth stimulated by standard increases will be 0.190 in logarithm, as shown in Table 3.9. This means that if firms kept the weight and engine power of their cars at the 2011 level, they will be able to build cars with 40.5 percent higher MPG in 2025 than in their 2011 products, or an increase of 0.340 in logarithm. However, the increases in CAFE standards for cars is 0.542 in logarithm, suggested a 0.2 gap or shortage in innovation. Therefore, to meet the new standards in 2025, automakers will have to decrease the weight and engine power of their cars compared to the 2011 level to gain better fuel economy. Compared to historical data, cars will have to be downsized to the 1995 level to be able to comply with the 2025 standards, assuming that firms lower weight and engine power backward of the same percentage they increased weight and engine power in the past.

Table 3.9. Prediction of future innovations from under new CAFE standards.

	Cars		Trucks	
	Percentage	logarithm	Percentage	logarithm
Average increase in the CAFE standards from 2011 to 2025	72.0%	0.542	55.6%	0.442
Average annual innovation	1.2%	0.012	0.7%	0.007
Innovation response rate to changes in CAFE standards	0.320		0.624	
Induced innovation	20.9%	0.190	37.4%	0.318
Total innovation from 2011 to 2025	40.5%	0.340	44.6%	0.369
Deficit to meet the 2025 targets	22.5%	0.203	7.6%	0.073

Likewise, I calculated the future innovation in the light truck sector. The total induced innovation will be 37.4 percent in the truck sector, or 0.318 in logarithm from

2011 to 2025, and the natural innovation will be 9.8 percent, or 0.093 in logarithm. There is only a 7.6 percent gap that would require downsizing to meet the 2025 targets. I estimate that firms only need to downsize their light duty trucks to the 2008 level to achieve that.

Discussion

In chapter two and three, I estimated the innovation in the automobile industry under the pressure of CAFE standards, and then I predicted changes in future vehicle attributes under the new aggressive standards. I found that automakers would have a higher innovation rate under the new standards. I also quantified the innovation response rates induced by the pressure from the tightened standards. In the truck sector, the induced innovation would be more sensitive to changes in the standards than in the car sector, even though the natural innovation rate is higher in the car sector. However, having a positive effect on innovation is not enough to conclude that the overall effect of the new aggressive standards would be positive. Further studies are necessary to investigate whether these induced innovations in fuel economy related technologies are at the expense of innovation in other areas, such as safety.

My simulation of innovation under the new aggressive CAFE standards suggested that automakers will have to do moderate downsizing to meet the 2025 target in cars, and they only need minor downsizing in trucks to meet the standards. This is a much more optimistic prediction than previous studies have shown.

Finally, by modeling innovation as a function of changes in regulation stringency, I present a tool that can be used in predicting future innovation under new regulations more precisely, and which could be used to compare between different scenarios in regulations by taking into account the rate of changes in the stringency levels. This method could also be applied to other areas with similar quantifiable standards or regulations as in the automobile industry.

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CHAPTER 4

FUNDING ROAD MAINTENANCE IN THE UNITED STATES:

VMT TAX AS AN ALTERNATIVE

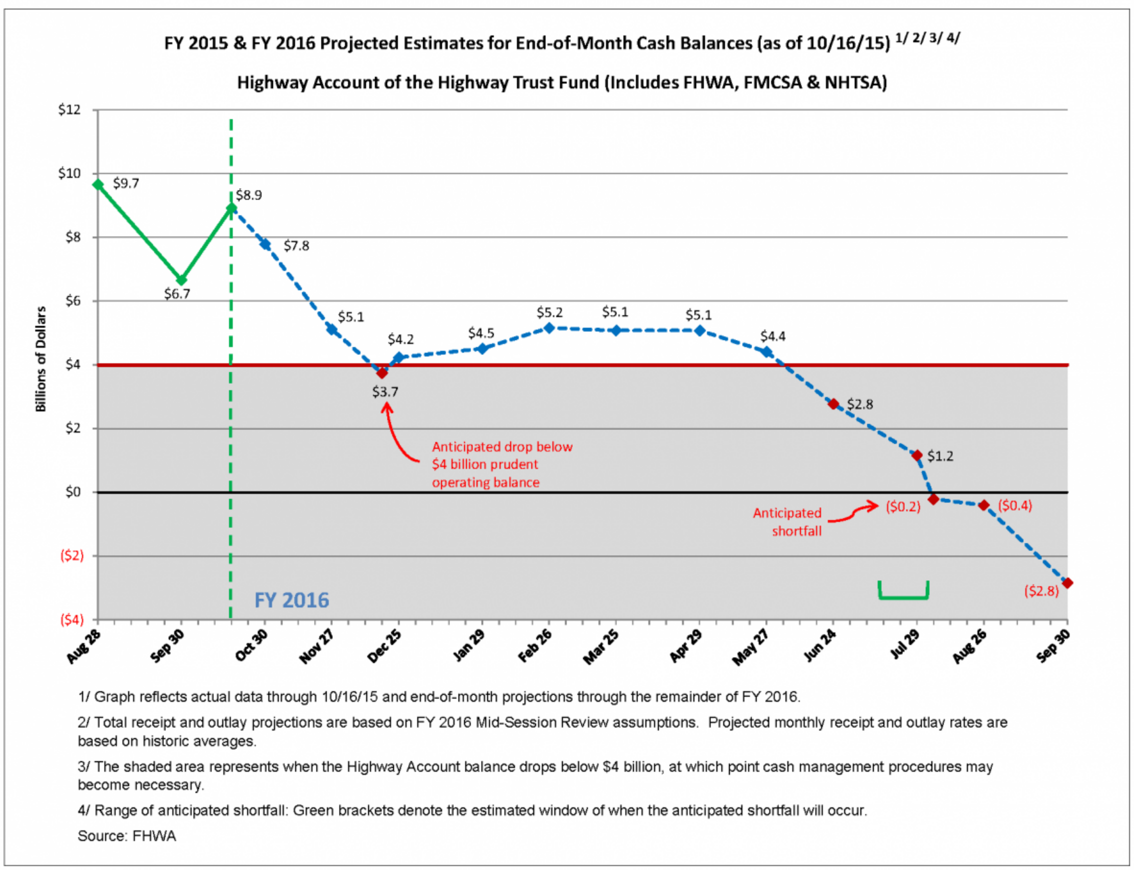
Introduction

The fuel economy of light duty vehicles that run in the United States has improved considerably in the past few decades, thanks to the CAFE standards. However, the improvement of fuel economy, along with an observed decline in driving, has led to persistently decreased revenue raised from gasoline taxes and posed a significant challenge for financing road maintenance services. The U.S. Department of Transportation has stated that the Highway Trust Fund is nearing insolvency. In 2015, on their official website, their ticker showed that the Highway Trust Fund would drop below safe levels by December[14] as shown in figure 4.1.

[14] Highway Trust Fund Ticker can be found at: https://www.transportation.gov/highway-trust-fund-ticker

In fact, the Department of Transportation made a similar prediction in 2014 and the crisis was averted by a huge transfer from the general account, which means money was borrowed from tax revenue of other sectors that may not necessarily use the road directly. With the new aggressive CAFE standards, pushed by the Obama administration, and the improvements in technology, average fuel economy of new vehicles will increase sharply before 2025 and make the gasoline tax revenue shrinkage problem even worse. In extreme cases, such as the introduction of electric vehicles, the users are not paying any gasoline tax at all while using the roads.

Figure 4.1 Highway Trust Fund Ticker



Although measures were taken or discussed to cover the shortage in road maintenance funding. While transferring from the general account was used as a temporary solution, it raised fairness concerns because those who rarely drive or don't drive at all have to subsidize those who drives more often. Raising gasoline tax seems to be the best solution economically. Economists believe that a higher gasoline tax rate would not only help raise the tax revenue but also better internalize the externality of driving, which includes pollution, congestion, accident, etc. However, considering the fact the average fuel economy of new vehicles will be over 50 percent higher than current models in the next decade, to fully compensate the revenue losses from the decreases in gasoline consumption requires the federal and state governments to make huge increases in the tax rate in a relatively short period of time. Such major increases in gasoline tax are not politically feasible. Unlike European countries, the general public in the United States is strongly against any form of gasoline tax increases. In fact, most politicians consider it political suicide to propose major increases in gasoline taxes. Another problem with an increased gasoline tax is that new innovation in the automobile industry allows automakers to provide their consumers with hybrid vehicles and electric vehicles, which have extremely high MPG compared to traditional internal combustion engine vehicles. The drivers of these highly efficient vehicles spend much less than the average driver on gasoline and thus pay much less gasoline tax. As the market share of hybrid and electric vehicles becomes larger, increases in the gasoline tax rate will have little effect on collecting tax revenue from the users of these new types of vehicles.

Therefore, to remedy this problem, introducing a VMT tax, which charges people based on the distance they drive instead of the gasoline they purchase, has received increased attention in the policy world. One traditional mechanism to charge driving by distance traveled and to raise funds is collecting toll fees. However, only a relatively small portion of roads, mostly highways, are suitable for setting up toll stations. Collecting toll fees on local roads, especially areas with multiple intersections can be disturbing and could affect the efficiency of road usage. Another way to charge driving by distance is to install electronic devices such as a GPS to record traveling distance and locations of traveling. The government can then use the recorded travelling information to calculate fees and bill the drivers. Oregon is the first state in the United States that imposed a voluntary VMT tax program in 2014 after experiments of pilot projects using this method. A GPS tracking device was installed on volunteered vehicles[15] and drivers were charge at a rate of 1.5 cents[16] per mile of their traveled distance in public roads[17]. However, such a method also raises privacy concerns because some people are afraid that the governments may abuse the recorded information considering they technically would have all the information of people's travelling records, including their whereabouts at any time, whether they were speeding, etc.

Despite the national discussion on the feasibility of replacing the per gallon based gasoline tax with a VMT tax, little research has been conducted in estimating the potential impact of this tax scheme at the national level. In this chapter, I explore how a nationwide uniform VMT tax would potentially alter households' driving behavior and tax revenue,

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[15] Installation cost of the GPS system is approximately $250 per vehicle.

[16] Oregon state government uses 20 as the average MPG of the state vehicle fleet. Their current state gasoline tax is 30 cents per gallon; therefore, the VMT tax rate was set at 1.5 cents per mile so it is equivalent to the gasoline tax rate payed by an average driver.

[17] Oregon frames the VMT tax as a road usage fee. Therefore, the government cannot charge people when they are driving on private roads. This is part of the reason why a GPS recording system is necessary in the project.

especially when the overall fleet fuel economy improves rapidly. My analysis includes two steps. The first is to use household survey data to assess households' sensitivity of driving demands to the changes in their driving costs, which is a combination of fuel costs and taxes. I used the 2009 NHTS to collect data on household owned vehicles and annual miles traveled as well as their socio-demographic information and regional characteristics. I also collected data on vehicle attributes including weight, class, horsepower, fuel economy using Ward's Automotive Yearbook 1971-2010 and data from www.automobile-catalog.com. I merged the two datasets and estimated how households with different types of vehicles would adjust their annual vehicle usage according to the changes in their driving costs. My results show that households with multiple vehicles are more sensitive to driving cost changes compared to households that only have one vehicle. The usage of SUVs and vans, which are more related to recreational purposes, are more sensitive to driving cost fluctuations than the usage of small cars, which are more related to daily commute.

Next, I used the estimates obtained in the first step to simulate the tax revenue and driving behavior change under different scenarios, including changes in gasoline tax rates, changes in pre-tax gasoline prices, and replacing the gasoline tax with a uniform VMT tax. A uniform VMT tax does not discriminate vehicle type or fuel economy of vehicles. I solved the per mile tax rates that would generate a similar amount of tax revenue as a gasoline tax does (this scenario is based on the VMT tax scheme adopted in Oregon) in each state. My results indicate that a VMT tax would be slightly more regressive than the current gasoline tax. The annual tax burden in low income households would slightly increase and the tax burden in high income households would slightly decline. This type of VMT tax would increase the driving costs of high MPG vehicles and decrease the driving costs of low MPG vehicles, which was criticized for creating a negative incentive on expending usage of efficient vehicles. However, my simulations also show that as because the overall fuel economy continues to increase, a VMT tax could provide a much more stable tax revenue without making any major adjustment in the tax rates. On the other hand, the current gasoline tax, would face a slide in tax revenue as fleet fuel economy improves.

This research contributes to the study on VMT taxation and adds to the literature of the rebound effect in driving behavior. More importantly, my work aims to inform the ongoing policy discussion on using a VMT tax as an infrastructure funding mechanism to offset the losses of gasoline tax revenue, resulting from increasingly fuel-efficient vehicles. This issue has become particularly urgent because the current CAFE standards seek to rapidly improve overall fuel economy and are expected to further bolster the usage of fuel-efficient vehicles and erode the tax revenue collected for road maintenance. My work suggests that a VMT tax may serve as a promising alternative to gasoline tax under the current regulations and environment in the United States.

Literature Review

In 2008, the federal gasoline tax was 18.4 cents per gallon and the state gasoline tax ranged from 7.5 cents to 37.5 cents per gallon[18]. Compared to the EU countries, the United Sstates had much lower tax rates on gasoline consumption. Parry and Small

[18] Georgia had the lowest state gasoline tax rate and Washington had the highest tax rate.

(2005) estimated that the optimal gasoline tax should be set at $1.01 per gallon in the United States to be able to internalize all the externalities of driving, including congestion costs, pollution costs, and accident costs. This tax rate is over 100% higher than the combined federal and state gasoline taxes in most states. Policy makers in the United States face great pressure from the general public when any form of gasoline tax increase is proposed. For example, the federal gasoline tax, had been fixed at 18.4 cents since 1997, regardless of the inflation in expenditures. Because raising gasoline taxes on a large scale is infeasible, people seek other methods to generate a more stable revenue for road maintenance costs. Therefore, taxes that are designed to charge people for their road usage instead of gasoline consumption became of great interest to researchers and policy makers.

There are several types of road pricing that charges drivers base on the distance they travel or even the time window in which they travel on certain routes. One of the most common is highway tolls, which typically charges highway users depending on the length they drive between where they enter and exit the highway. In some highly congested areas, local governments also charge congestion fees/peak-period fees during peak hours as a tool to manage driving demand and gain tax revenue during the process. The uniform VMT tax I explore in this chapter is also a form of road pricing. However, unlike highway toll fees, which are only implemented on certain routes, I look into a more general tax that applies to all driving to replace the current gasoline tax. This uniform tax set a per mile based tax rate regardless of vehicle model and fuel economy of all light duty vehicles.

Dozens of pilot programs of mileage based taxation were implemented across the nation in the late 2000s and early 2010s when the federal government and state governments realized their gasoline tax revenues were at risk because of the improved efficiency of new vehicles, which is a direct result of more stringent CAFE standards. Pilot programs were run to assess the feasibility of technologies and the attitude of the participants. GPS systems were installed on the participating vehicles in these programs to record distance and jurisdiction of all vehicle use and the participants were charged accordingly. Studies on these pilot programs suggested that most participants had a more positive view of the mileage based tax after experiencing the programs. However, there was also a higher cost to collect tax revenue compared to the pay-at-pump gasoline tax, mainly because of the extra technology requirements.

After a pilot program in 2012, Oregon passed the Senator Bill 810 in 2013 and established the first mileage-based revenue program for light duty vehicles in the US. They began a state wide voluntary VMT tax program in 2015[19]. The tax was framed as a road usage fee used to repair damaged roads. A uniform tax rate was set at 1.5 cents per mile regardless of vehicle type and model. Drivers were only charged for their driving on Oregon's public roads and the GPS systems installed recorded all the distance and routes they traveled. Participants of the program received monthly bills of their road use charges and had the state gasoline tax refunded when they purchased gasoline at pumps in Oregon. In this chapter, I focus on a uniform VMT tax that is very similar to what Oregon adopted to replace both the federal and state gasoline taxes.

[19] The current program is called OReGO: http://www.myorego.org/.

To simulate driving demands and then calculate tax revenue under different taxes, I estimated vehicle usage changes with respect to changes in post-tax driving costs using household survey data. This part of the study also contributes to the literatures of the rebound effect, which looks into the relationship between fuel costs and driving demands. The estimated elasticities of driving distance with respect to fuel price range from 0.05 to 0.87 in various studies. Greene (1992) used annual U.S. data to estimate the rebound effect at 0.05 to 0.15 in both the long run and short run. He also found evidence that the elasticities decline over time. Using the same data, Jones (1993) estimated a long run elasticity of 0.31 and a short run elasticity of 0.11. Schimek (1996) accounted for CAFE standards and also used the annual U.S. data. He estimated a long run elasticity of 0.29.

In studies that used less aggregated data, Haughton and Sarkar (1996) obtained a rebound effect of 0.16 in the short run and 0.22 in the long run. West (2004) estimated a rebound effect of 0.87 using the 1997 Consumer Expenditure Survey data. On the other hand, Pickrell and Schimek (1999) studied the 1995 Nationwide Personal Transportation Survey (NPTS), which resulted in a rebound effect of 0.04 by Su (2012) obtained a short run elasticity of 0.03 and a long run elasticity of 0.11 using the 2009 NHTS data. Overall, most long run rebound effect estimates fell in the vicinity of 0.2-0.3, while short run effects varied among studies that used different data and methods.

Empirical Model

The major purpose of this study is to compare changes in tax revenue under different tax mechanisms and tax rates. To make such a comparison, quantitative estimates of driving demand and tax revenue under different scenarios are key to the simulation. I modeled the annual usage or driving demand in terms of vehicle miles traveled in individual household vehicles as the following,

$$M_{ij} = f(GP_j, T_{ij}, X_j) \tag{1}$$

where M_{ij} is the annual VMT of individual vehicle i in household j, GP_j is the fuel cost an individual household faces, T_{ij} is the type of individual vehicle i, and X_j is the set of socio-demographic and regional information of household j. The fuel cost I used here is the self-reported average annual post-tax fuel cost of households, in terms of dollar per gallon. There are two reasons I used self-reported fuel cost from the survey data. The first is that more detailed annual average at-pump gasoline price at the zip code level is not publicly available. Therefore, compared to using more aggregated gasoline price data, household level data can provide more region specific information. The second is that even for households living in the same area, fuel prices vary because of their commute behaviors, route preferences, and gasoline station preferences[20]. Therefore, the self-reported fuel costs better reflect the self-realized, and household specific driving costs, which is one of the key elements that affect vehicle usage in households. This is further discussed in the data section. Vehicle type describes the vehicle category of individual vehicles. In this study, I divided all light duty vehicles into five categories: small cars, large cars, pickups, SUVs, and vans. At certain levels, vehicle type reflects a household's the type of traveling. For example, vans and SUVs are more often used for family trips while small cars, which usually have relatively high MPG, are more often used for the

[20] For example, a driver who lives and works in New York City often may choose to purchase gasoline from New Jersey to save costs. In such cases, using the gasoline cost reported by the driver might be more accurate than using the average gasoline price of his residence area.

daily commute. Socio-demographic information includes annual income of sampled households, education, race, and age group of household respondents, life cycle[21] of households, number of workers and number of drivers in households, and respondent's distance to work. Reginal information includes the population density of households' residence areas, the size of metropolitan statistical area (MSA)[22], whether the household lives is located in a rural area and whether there is rail service in the area.

Following an approach similar to Su (2012), I model the first empirical model as the following,

(2) $\ln(M_{ij}) = \beta \ln(GP_j) + X_j' B + e_{ij}$

In this model, the dependent variable is log annual VMT. The benefit of using log annual VMT and log gasoline price is that the coefficient of log gasoline price can be directly interpreted as the elasticity of an annual VMT with respect to gasoline price. These estimates can be used to compare with previous studies in rebound effect as a check of data quality. To further explore the heterogeneity of driving demand elasticities among different types of vehicles, I added a set of vehicle category dummies and interacted them with the gasoline price and extended the empirical model as,

(3) $\ln(M_{ij}) = \beta \ln(GP_j) + GP_j * T_i'B_1 + T_i'B_2 + X_j'B_3 + e_{ij}$

T is a set of vehicle type dummies, which include large car, pickup, SUV, and van. So β represents the elasticity of an annual VMT of small cars with respect to gasoline price.

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[21] In NHTS data, life cycle describes the composition of a household. It reports the number of elders, adults and children in a household.

[22] Metropolitan statistical areas are geographic entities delineated by the Office of Management and Budget (OMB). MSA is used by Federal statistical agencies in collecting statistics. A metro area contains a core urban area of 50,000 or more population. The historical delineation of MSA can be found on the U.S. Census Bureau website: http://www.census.gov/population/metro/data/pastmetro.html

The linear combination of β_1 and T_i'B_1 represent the elasticities of driving demand in other vehicle categories.

To better simulate and provide more straight forward estimates of driving demand with respect to fuel cost changes, I modeled the second empirical model as the following,

(4) $M_{ij} = \beta\ GP_j + X_j'\ B + e_{ij}$

In this model, I regressed the annual VMT on gasoline price instead of using log annual VMT and log gasoline price. The benefit of this model is that the coefficients of gasoline prices provide a direct mileage estimate of driving demand in response to gasoline price change in dollar terms. Similarly, I also added vehicle category dummies and interacted them with the gasoline price to further estimate driving responses in different types of vehicles,

(5) $M_{ij} = \beta\ GP_j + GP_j * T_i'B_1 + T_i'B_2 + X_j'B_3 + e_{ij}$

As discussed in formula (3), β represents the response rate of small cars when facing changes in fuel costs and the response rates of other types of vehicles are the linear combination of β and T_i'B_1.

Because this study focuses on the estimation of tax revenue collected from using vehicles, I only kept households that possess vehicle(s) in the data. I further divided these households into two different types, single vehicle households and multiple vehicle households. In single vehicle households, family members have fewer options when facing fuel cost changes compared with multiple vehicle households. Thus, I ran empirical models (2)-(5) separately in these two types of households to compare the differences in their responses.

Data

In this paper I used the 2009 NHTS data to obtain households' socio-demographic information, regional information of their residences, fuel costs households faced, as well as their vehicle choices and annual usages. I then used data from WAY and AC to ascertain more detailed information of vehicle models.

2009 NHTS data

The NHTS was conducted by the Federal Highway Administration (FHWA) of the U.S. Department of Transportation (US DOT) in 2001 and 2009. I focused on the 2009 survey data to make an analysis that reflects the most recent behavior of households. The NHTS data include information on travel demands as well as socio-demographic of sampled households. A random digit dialing (RDD) sampling procedure was used to initially select the national sample of household participants, as well as to conduct follow-up household and personal phone surveys for the national sample. Additional "add-on" surveys were conducted in certain regions by request. Although households were the sampling unit, many households had multiple drivers and passenger vehicles for which I used both individual data and household level data.

The 2009 NHTS sample includes 25,510 households in the original national sample and 124,637 households in the add-on sample. Households that claimed to own vehicles were also asked to provide detailed information about their vehicles, their usage, as well as fuel prices they faced. The published data contain three separate files, household, individual, and vehicle files. The vehicle file records information regarding vehicle type, make, model, and model year, all of which are reported using the NHTSA coding system. Using these model codes, I merged additional vehicle attribute information that were primarily collected from WAY and AC data. Despite my best efforts, in some cases I was unable to match some of the vehicles in the NHTS data with the WAY and AC data because of missing or incorrectly coded or reported vehicle make, model, and/or year. I succeeded in matching 91.9 percent of total passenger vehicles in the 2009 NHTS.

I then made a series of cleaning steps in the merged data. I removed unmatched vehicles for which I did not have vehicle attribute information and thus could not be used in the analysis. I also dropped households that have unreliable information, such as reporting unreasonably high total annual vehicle usage, per driver annual miles traveled, or fuel prices. Detailed steps of data merging, data cleaning, and sample statistics are provided in the appendix.

Vehicle attribute data (WAY and AC)

I collected attribute data from WAY of all vehicles sold in the U.S. market between 1971 and 2011 and from AC between 1945 and 2011. The data source is the same as the vehicle attribute data I used in chapter one but the data I used here cover a longer period of time. I used both data to include as many vehicle models as possible so I could accurately match vehicle attributes with vehicles reported in the NHTS data. I then made several cleaning steps before merging the vehicle attribute data with the household survey data. Similar to what I did in chapter two, I constructed the fuel type of all internal combustion vehicles using the reported compression ratio. I assigned fuel type as gasoline if the compression ratio of the engine is less than 12 and as diesel if the compression ratio is above 12. I also constructed transmission type for earlier years in WAY when several transmissions were reported for the same trim. I picked only the first reported transmission as the standard trim to determine whether the vehicle model used a manual transmission or an automatic transmission.

In the WAY data, the MPG reported reflect the EPA adjusted MPG ratings. Because the EPA changed their method for estimating MPG ratings over time, only the combined adjusted MPG rating is reported before 1985. Beginning in 1985, adjusted MPGs were reported as two different variables, the city MPG and the highway MPG. The city MPG was calculated as 0.9 * EPA tested city MPG and highway MPG was calculated as 0.78 * EPA tested highway MPG.

In 2008, the EPA adjusted their MPG rating methods again. This new method took more variables, such as outdoor temperature and air-conditioning, into account. This change resulted in a decrease in EPA adjusted MPG for most vehicles. The new formulas used by the EPA were:

$$\text{Adjusted city MPG} = \frac{1}{0.003259 + \frac{1.1805}{\text{Tested city MPG}}},$$

$$\text{Adjusted highway MPG} = \frac{1}{0.001376 + \frac{1.3466}{\text{Tested highway MPG}}}.$$

I used these formulas and the adjusted MPG to reverse compute tested MPG and then applied the formulas used prior to 2008 to obtain adjusted MPG numbers that are comparable to those for previous model years. I applied the same method the EPA used to construct combined MPG, which is the weighted harmonic mean of adjusted city MPG and adjusted highway MPG using a city/highway ratio of 0.55/0.45.

The AC data do not report the EPA MPG ratings but rather provide engineering derived fuel economy estimates. I calculated the combined MPG using city MPG and highway MPG reported in the AC data using the same city/highway ratio of 0.55/0.45. Compared with the WAY dataset, combined MPG in the AC dataset is much lower for similar vehicle models of the same model year because of the difference in estimation methods. To address this difference, I estimated the average differences in MPG between the two data sets by vehicle classes. Following Knittel (2011), I controlled for vehicle attributes related to MPG, such as horsepower, curb weight, torque, transmission type, and fuel type. The precise econometric specification used is:

$$(6) \quad \ln MPG_{it} = T_t + \beta_1 \ln W_{it} + \beta_2 \ln HP_{it} + \beta_3 \ln Q_{it} + \beta_4 M_t + \beta_5 M_t * t + \beta_6 D_{it} + \beta_7 WAY_{it} + X'_{it}B + \epsilon_{it,}$$

where MPG is the fuel economy of the vehicle, T is the model year, W is the curb weight, HP is the horsepower, Q is the torque, M is a dummy for manual transmission, D is a dummy for diesel fuel use, and WAY is a dummy for the WAY dataset that equals one if the observation is from the WAY dataset. X includes dummies for different manufactures.

The WAY dataset does not report vehicle torque before 1997, so using specification one only allows vehicles after 1996 in the WAY dataset to enter the regression. To include more vehicles prior to model year 1997, I also considered a second specification which removed torque from formula (6) and only used horsepower as the measure of engine output[23]:

$$(7)\quad \ln MPG_{it} = T_t + \beta_1 \ln W_{it} + \beta_2 \ln HP_{it} + \beta_3 M_t + \beta_4 M_t * t + \beta_5 D_{it} + \beta_6 WAY_{it} + X'_{it}B + \epsilon_{it}.$$

Table 4.1 reports the regression results of both specifications in cars and table 4.2 reports the regression results of light duty trucks in the WAY and the AC data. The coefficients

Table 4.1. Estimation of MPG differences between AC and WAY data (cars).

	Small Cars		Medium Cars		Large Cars	
	SP 1	SP 2	SP 1	SP 2	SP 1	SP 2
Log horsepower	-0.1490	-0.4480	-0.1310	-0.4640	0.0190	-0.4470
	-(.0750)	-(.0140)	-(.0330)	-(.0140)	-(.0330)	-(.0240)
Log weight	-0.2980	-0.5250	-0.2990	-0.5630	-0.1560	-0.4090
	-(.0580)	-(.0440)	-(.0530)	-(.0430)	-(.0410)	-(.0920)
Log torque	-0.4120		-0.4670		-0.6670	
	-(.0990)		-(.0370)		-(.0530)	
Manual transmission	0.0580	0.0590	0.0420	0.0460	0.0780	0.0880
	-(.0060)	-(.0060)	-(.0110)	-(.0100)	-(.0060)	-(.0120)
Manual transmission*t	-0.0030	-0.0030	-0.0020	-0.0020	0.0010	0.0010
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	-(.0010)
Diesel engine	0.2740	0.2020	0.0890	0.0290	0.1650	0.1530
	-(.0560)	-(.0290)	-(.0540)	-(.0510)	-(.0080)	-(.0240)
WAY data dummy	0.3700	0.3370	0.4230	0.3850	0.5140	0.4910
	-(.0190)	-(.0180)	-(.0120)	-(.0130)	-(.0070)	-(.0130)
Turbo charged	0.1520	0.0900	0.1940	0.0940	0.2920	0.0170
	-(.0220)	-(.0190)	-(.0170)	-(.0440)	-(.0170)	-(.1060)
Year fixed effect	Y	Y	Y	Y	Y	Y
Manufacture fixed effect	Y	Y	Y	Y	Y	Y
Number of observation	15273	16871	15235	16372	17440	17794
R-squared	0.9307	0.9245	0.9509	0.9448	0.9309	0.9189

Note: The coefficient of WAY data dummy estimates the difference in MPG rating due to differences in estimation methods in cars after controlling for other vehicle attributes. Positive coefficient suggests that the MPG rating in WAY data is higher than that of AC data for similar models.

[23] Horsepower and torque are highly correlated variables. Horsepower=torque*Revolution per minute (RPM)/5,250. The horsepower and torque reported in the AC and the WAY data are the maximum horsepower and the maximum torque of the engine, which typically occur at different RPM levels.

of the “WAY data” dummy in all regressions provide the average differences of log MPG between the AC and WAY datasets in each vehicle class after controlling for other vehicle attributes. The differences between the coefficients of the “WAY data” dummy are small across the two specifications for each vehicle class. Considering that specification two covers a longer time period than the WAY dataset and thus covers more

Table 4.2. Estimation of MPG differences between AC and WAY data (trucks).

	Pickups		SUV/CUV		Vans	
	SP 1	SP 2	SP 1	SP 2	SP 1	SP 2
Log horsepower	0.1180	-0.2280	0.0980	-0.2970	0.1590	-0.2390
	-(.0490)	-(.0140)	-(.0520)	-(.0310)	-(.0700)	-(.0640)
Log weight	-0.2510	-0.4660	-0.3460	-0.6080	-0.6480	-0.6370
	-(.0470)	-(.0230)	-(.0310)	-(.0380)	-(.0330)	-(.0680)
Log torque	-0.4270		-0.5360		-0.4230	
	-(.0590)		-(.0650)		-(.0870)	
Manual transmission	0.0410	0.0700	0.0610	0.0470	0.0880	0.0490
	-(.0180)	-(.0320)	-(.0040)	-(.0050)	-(.0330)	-(.0270)
Manual transmission*t	-0.0020	-0.0040	-0.0030	-0.0020	-0.0030	-0.0020
	-(.0010)	-(.0020)	(.0000)	(.0000)	-(.0010)	-(.0010)
Diesel engine	0.3000	0.1330	0.3880	0.2350		
	-(.0080)	-(.0120)	-(.0670)	-(.0640)		
WAY data	0.4010	0.4230	0.4180	0.3990	0.3520	0.2940
	-(.0100)	-(.0030)	-(.0160)	-(.0160)	-(.0210)	-(.0240)
Turbo charged	0.0420	-0.0230	0.1600	0.0650		
	-(.0130)	-(.0070)	-(.0170)	-(.0140)		
Year fixed effect	Y	Y	Y	Y	Y	Y
Manufacture fixed effect	Y	Y	Y	Y	Y	Y
Number of observation	4296	5413	9358	9958	1772	2523
R-squared	0.8201	0.7711	0.9122	0.8882	0.9173	0.8309

Note: The coefficient of WAY data dummy estimates the difference in MPG rating due to differences in estimation methods in cars after controlling for other vehicle attributes. Positive coefficient suggests that the MPG rating in WAY data is higher than that of AC data for similar models.

vehicle models recorded in the NHTS data, I used the estimated coefficients of “WAY data" dummy in specification two to adjust the reported MPG in the AC data. This resulted in MPG increases of 40 percent in small cars, 47 percent in medium cars[24], 63 percent in large cars, 53 percent in pickups, 49 percent in SUV/CUV[25], and 34 perent in vans of the AC data. I made these adjustments to remove the differences in MPG rating that were caused by different calculation methods so the vehicle fuel economy information in the AC data are comparable to that of the WAY data.

Vehicle distribution in households

After removing all households that do not own vehicles and those with missing or questionable information in key household socio-demographic and/or regional information, there were a total of 94,645 households and 207,382 vehicles left in my final sample of analysis among 48 states[26]. As shown in table 4.3, in households with multiple vehicles, the fleet consisted of a relatively high percentage of light duty trucks, including pickups, SUVs and vans. On the other hand, over 54% of the vehicles in single vehicle households are from the small cars category. In all households, small cars have a mean MPG of over 27, while other types of vehicles only have a mean MPG in the vicinity of 20. Also, average fuel economy is slightly higher in single vehicle households in all vehicle categories.

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[24] In this study, I combined the small cars and the medium cars into the small cars category. This is because their roles in households are similar.
[25] In this study, I combined SUV and CUV in the same category as they serve similar travelling purposes in households.
[26] Hawaii and Iowa are not included in this study because of the incomplete regional and tax rate information in the NHTS data.

Table 4.3. Vehicle composition in single vehicle and multiple vehicle households.

Vehicle type	Single vehicle households			Multiple vehicle households		
	Count	Percentage	Mean MPG	Count	Percentage	Mean MPG
Small cars	17,105	54.9%	27.4	69,005	39.2%	27.1
Large cars	4,273	13.7%	21.9	14,802	8.4%	21.8
Pickups	2,285	7.3%	20.0	38,294	21.7%	19.5
SUVs	5,217	16.7%	20.9	39,381	22.3%	19.8
Vans	2,294	7.4%	20.5	14,726	8.4%	20.3
Total	31,174		24.5	176,208		22.8

Table 4.4. Vehicle distribution across income groups.

Household annual income	Number of households	Percentage of single vehicle households	Percentage of vehicle type				
			Small cars	Large cars	Pickups	SUVs	Vans
< 5000	1025	70.2%	47.9%	12.5%	17.6%	14.0%	8.1%
5000-9999	2437	72.0%	49.8%	12.4%	18.3%	11.5%	8.0%
10000-14999	4158	69.4%	47.9%	12.5%	18.8%	13.3%	7.5%
15000-19999	4826	61.5%	45.0%	13.2%	19.7%	13.8%	8.4%
20000-24999	4349	56.9%	45.0%	12.7%	19.5%	14.6%	8.2%
25000-29999	6385	46.8%	41.3%	12.9%	21.6%	15.6%	8.6%
30000-34999	3774	42.7%	41.0%	11.7%	21.8%	16.6%	8.9%
35000-39999	6216	36.1%	39.9%	11.5%	22.4%	17.6%	8.6%
40000-44999	3242	33.0%	39.8%	10.0%	22.3%	19.0%	8.9%
45000-49999	6222	28.6%	39.0%	10.9%	23.1%	18.8%	8.2%
50000-54999	2924	26.5%	40.0%	9.2%	22.6%	20.0%	8.2%
55000-59999	5623	21.5%	39.6%	9.3%	22.3%	20.7%	8.2%
60000-64999	2198	19.2%	40.0%	8.0%	22.3%	21.3%	8.4%
65000-69999	4843	16.9%	39.2%	9.1%	21.0%	22.3%	8.4%
70000-74999	2250	14.7%	39.5%	7.7%	21.7%	23.0%	8.2%
75000-79999	4592	13.2%	40.1%	8.0%	20.7%	23.2%	8.0%
80000-99999	9231	9.2%	39.8%	6.7%	19.9%	24.5%	9.1%
≥ 100000	20350	5.9%	42.9%	6.6%	14.9%	28.1%	7.5%

Vehicle choices in households are also highly related to household income. As reported in table 4.4, over 70 percent of households that have an annual income below

$10,000 and own a vehicle have only one vehicle. Meanwhile, over 94 percent of households that have an annual income above $100,000 own multiple vehicles. Low income households are also more likely to choose cars compared to high income households, over 60 percent vehicles in households with an annual income below $15,000 are small cars or large cars while less than 50 percent of vehicles in high income households are cars. High income households are not only more likely to own multiple vehicles but they are also more likely to own SUVs, which are often used for family trips. In households with an annual income above $100,000, 28 percent of their vehicles are SUVs, two times the rate in low income households.

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CHAPTER 5

VMT TAX SCENARIOS SIMULATION

Introduction

In this chapter, I present and discuss the regression results of the empirical models discussed in chapter four. The results of these regressions indicate how household vehicle usage responded to the variations in fuel costs. Next, I use the estimates obtained from these estimates to solve for VMT tax rates in each state that would generate the same tax revenue as the current gasoline tax. Finally, I predict changes in driving under different tax and fuel economy scenarios, and thus estimate tax revenues under various settings.

Regression results

Table 5.1 shows the regression results of model (2) and (3), of which the dependent variable is log annual VMT. Model (3) also includes interaction terms of fuel costs and vehicle type dummies. I also compared the different responses in single vehicle households versus responses in households with multiple vehicles.

In the results of model specification (2), the coefficients of log gasoline price represent the elasticity of driving demand with respect to change in fuel cost, or the rebound effect. My estimation of the whole fleet is -0.476. In households with multiple vehicles, the demand is more elastic with an elasticity of -0.577. However, in single vehicle households, the demand is very inelastic. The elasticity of driving demand is only -0.162 and not significantly different from zero.

In model specification (3), the coefficients of log gasoline price show the baseline elasticity of small cars in households and the interaction term of other vehicle type dummies and gas price show the difference between the elasticities of other vehicles and small cars. The actual elasticity of vehicles other than small cars should be the linear combination of the baseline elasticity and the corresponding interaction terms. I tested the linear combination of these interaction terms and the baseline and table 5.2 indicate the elasticities of all types of vehicles.

Table 5.1. Household vehicle usage (Annual VMT) response to fuel cost change (log).

	Single vehicle		Multiple vehicle		All	
	(3)	(2)	(3)	(2)	(3)	(2)
Log Gas Price	-0.186	-0.162	-0.298	-0.557	-0.243	-0.476
	(.167)	(.127)	(.089)	(.062)	(.079)	(.057)
Large car	-0.492		0.684		0.374	
	(.417)		(.255)		(.220)	
Pickup	0.094		-0.022		-0.008	
	(.471)		(.153)		(.144)	
SUV	0.616		0.285		0.343	
	(.343)		(.147)		(.135)	
Van	-0.544		1.155		0.970	
	(.534)		(.225)		(.209)	
Log GP*Large car	0.414		-0.598		-0.331	
	(.373)		(.229)		(.198)	
Log GP*Pickup	0.018		-0.123		-0.140	
	(.420)		(.136)		(.129)	
Log GP*SUV	-0.440		-0.134		-0.188	
	(.305)		(.131)		(.121)	
Log GP*Van	0.576		-0.902		-0.744	
	(.476)		(.202)		(.187)	
Log population density	-0.063	-0.066	-0.035	-0.032	-0.035	-0.031
	(.005)	(.005)	(.002)	(.002)	(.002)	(.002)
Number of worker	0.075	0.077	-0.001	-0.001	-0.001	-0.001
	(.015)	(.015)	(.004)	(.004)	(.004)	(.004)
Household size	0.024	0.032	0.001	0.010	0.007	0.017
	(.016)	(.015)	(.005)	(.005)	(.005)	(.005)
Number of driver	0.145	0.146	0.036	0.026	0.016	0.005
	(.017)	(.017)	(.007)	(.007)	(.006)	(.006)
Log distance to work	0.141	0.140	0.128	0.124	0.129	0.125
	(.006)	(.006)	(.002)	(.002)	(.002)	(.002)
Rail in area	-0.053	-0.064	-0.059	-0.046	-0.062	-0.050
	(.020)	(.020)	(.010)	(.010)	(.009)	(.009)
Rural	0.071	0.079	0.033	0.027	0.033	0.027
	(.017)	(.017)	(.008)	(.008)	(.007)	(.007)
Male household respondent	0.213	0.224	0.043	0.041	0.053	0.047
	(.011)	(.011)	(.005)	(.005)	(.005)	(.005)
Income fixed effect	Y	Y	Y	Y	Y	Y
Age fixed effect	Y	Y	Y	Y	Y	Y
Education fixed effect	Y	Y	Y	Y	Y	Y
Race fixed effect	Y	Y	Y	Y	Y	Y
Life cycle fixed effect	Y	Y	Y	Y	Y	Y
MSA size fixed effect	Y	Y	Y	Y	Y	Y
Obs	31174	31174	176208	176208	207382	207382
R squared	0.2061	0.2029	0.1106	0.1005	0.1162	0.1068

Notes: The dependent variable is log annual VMT.

Table 5.2. Annual VMT elasticity (with respect to gasoline price) change.

	Single vehicle	Muti-vehicle	All
Small car	-0.186	-0.298	-0.243
	(.167)	(.089)	(.079)
Large car	0.228	-0.896	-0.575
	(.341)	(.218)	(.187)
Pickup	-0.168	-0.422	-0.384
	(.390)	(.111)	(.108)
SUV	-0.626	-0.433	-0.431
	(.267)	(.110)	(.103)
Van	0.390	-1.200	-0.988
	(.453)	(.190)	(.615)

Note: The elasticities of small cars are the coefficients of log gasoline price in table 5.1. The elasticities of other vehicles are the linear combinations of log gasoline price and the interaction terms of gasoline price and corresponding vehicle category dummies in table 5.1.

The results suggest in single vehicle households, vehicle usage is overall less elastic than that of multiple vehicle households. In fact, in single vehicle households, only the elasticity of the SUV is significant, which is estimated to be -0.626. In multiple vehicle households, vehicle usage responses are all significant in all vehicle categories, with the driving demand of small cars being the least elastic and demand of vans being the most elastic. Multiple vehicle households normally have more options than single vehicle households in traveling options when facing fuel cost changes, such as within household carpooling or adjusting vehicle choices. For example, couples may drive only one car to go to work instead of driving separate vehicles when fuel cost increases. Also, multiple vehicle households may choose to use the vehicle that is relatively more efficient in the household when driving becomes more expensive.

The results also suggest that households' responses to gasoline costs vary among different vehicle types. Choices of vehicle type are related to its function in households, especially in multiple vehicle households. Small cars, which usually have high MPG, are used more often for daily commute, which has very inelastic driving demand, while SUVs and vans are used more for recreational purposes, such as family trips, which are more elastic in traveling demand. Such differences are important when exploring the effect of replacing gasoline tax with a uniform VMT tax, which would have different impact on driving costs in different types of vehicles.

Table 5.3 reports the regression results using model specification (4) and (5), which use annual VMT and fuel cost instead of their log forms. In model specification (4), the coefficients of gasoline price can be interpreted as the average change in annual mileage driven of an individual vehicle when facing $1 increase in per gallon gasoline cost. Similar to the results from using model specification (2) and (3), households with multiple vehicles responded much stronger to gasoline cost changes than single vehicle households. In specification (5), the coefficients of gasoline price are the baseline response rate of small cars and the response rate of other types of vehicles are the linear combination of the coefficients of gasoline price and the coefficients of the corresponding interaction terms of gasoline price and vehicle type dummies. I report the response rates of all vehicle types in table 5.4.

Table 5.3. Household vehicle usage (Annual VMT) response to fuel cost change.

	Single vehicle		Multiple vehicle		All	
	(5)	(4)	(5)	(4)	(5)	(4)
Gas Price	-666.0	-945.0	-636.4	-1378.0	-581.7	-1270.5
	(375.3)	(304.7)	(227.9)	(158.1)	(198.6)	(143.1)
Large car	-1637.6		3357.8		2101.4	
	(2627.5)		(1702.9)		(1452.7)	
Pickup	1552.4		757.9		726.8	
	(3409.8)		(1077.8)		(1009.2)	
SUV	7021.1		3262.6		3724.9	
	(2465.1)		(1081.9)		(989.1)	
Van	461.4		9353.4		8343.9	
	(3598.6)		(1595.6)		(1463.4)	
GP*Large car	515.1		-1024.0		-637.5	
	(858.2)		(557.9)		(475.6)	
GP*Pickup	-174.1		-478.1		-470.6	
	(1108.4)		(350.6)		(328.2)	
GP*SUV	-2049.3		-806.4		-959.2	
	(797.4)		(351.7)		(321.3)	
GP*Van	40.2		-2754.2		-2440.6	
	(1169.0)		(518.5)		(475.5)	
Log population density	-497.6	-515.4	-388.2	-372.3	-376.4	-361.1
	(35.3)	(35.4)	(19.6)	(19.5)	(17.5)	(17.4)
Number of worker	186.7	197.4	-107.8	-107.7	-121.0	-122.6
	(128.4)	(128.4)	(36.2)	(36.2)	(34.7)	(34.7)
Household size	486.4	526.9	176.5	229.2	221.1	275.2
	(149.3)	(148.2)	(43.1)	(42.8)	(40.7)	(40.5)
Number of driver	1078.0	1081.3	176.0	115.5	62.6	-2.5
	(138.9)	(139.1)	(58.5)	(58.3)	(52.3)	(52.2)
Distance to work	108.0	108.1	69.5	68.1	1172.8	71.2
	(34.2)	(34.0)	(6.4)	(6.3)	(19.2)	(6.3)
Rail in area	-571.3	-651.9	-512.7	-446.4	-535.3	-481.3
	(154.4)	(154.3)	(87.5)	(86.7)	(77.9)	(77.3)
Rural	571.7	619.9	408.9	382.9	409.7	384.7
	(128.0)	(128.0)	(62.8)	(62.8)	(57.3)	(57.2)
Male household respondent	1266.7	1368.4	202.7	192.4	286.9	260.4
	(90.3)	(88.7)	(41.5)	(41.5)	(37.6)	(37.6)
Income fixed effect	Y	Y	Y	Y	Y	Y
Age fixed effect	Y	Y	Y	Y	Y	Y
Education fixed effect	Y	Y	Y	Y	Y	Y
Race fixed effect	Y	Y	Y	Y	Y	Y
Life cycle fixed effect	Y	Y	Y	Y	Y	Y
MSA size fixed effect	Y	Y	Y	Y	Y	Y
Obs	31174	31174	176208	176208	207382	207382
R squared	0.1867	0.1843	0.1037	0.0993	0.1123	0.1082

Notes: The dependent variable is annual VMT.

Table 5.4. Annual VMT response rate with respect to gasoline cost change.

	Single vehicle	Multiple vehicle	All
Small/Medium car	-665.9784	-636.4166	-581.6978
	(375)	(228)	(199)
Large car	-150.9252	-1660.394	-1219.179
	(791)	(523)	(444)
Pickup	-840.0548	-1114.471	-1052.256
	(1053)	(283)	(275)
SUV	-2715.309	-1442.824	-1540.883
	(726)	(302)	(281)
Van	-625.803	-3390.664	-3022.249
	(1124)	(489)	(451)

Note: The response rates of small cars are the coefficients of gasoline price in table 5.3. The response rates of other vehicles are the linear combinations of gasoline price and the interaction terms of gasoline price and corresponding vehicle category dummies in table 5.3.

The results are also similar to that of the log form regressions. Multiple vehicle households responded to gasoline cost changes significantly in all vehicle categories and responded stronger in large cars, and vans than single vehicle households. Single vehicle households only responded strongly in SUV usage. The response rates in small cars are very similar in both types of households (-666 in single vehicle households versus -636 in multiple vehicle households). Because gas taxes were set at cents per gallon and the uniform VMT tax is also in the form of cents per mile, I use the regression results of model specification (4) and (5) to perform the following simulations under various situations.

Tax revenue simulation results

In this section, I simulated the gasoline consumption, vehicle usage, and tax revenue using the estimates obtained from the regression results from the previous section. I explored several scenarios in my simulation. The first was replacing the current federal and state gasoline taxes with a VMT tax that would generate the same tax revenue in each state. I then explored how tax revenue would change under the current gasoline tax and the VMT tax because fleet fuel economy in the United Sstates continues to increase. I also compared how tax revenue would be affected when facing pre-tax gasoline price fluctuations. Finally, I simulated raising the current gasoline tax to the optimal gasoline tax rate suggested by Parry and Small (2005).

Replacing gasoline tax with a uniform VMT tax

The major purpose of replacing gasoline tax with a VMT tax is to provide a more stable tax structure. In this part of my analysis, I first solved for a set of VMT tax rates for each state so they would generate the same amount of tax revenue as the gasoline tax revenue in each state. Within each state, I first calculated the total gasoline consumption in each state using the reported annual usage of each vehicle and its fuel economy. I then calculated the combined federal and state gasoline tax revenue collected in each state using the corresponding per gallon gasoline tax rates and the computed gasoline consumption.

A uniform VMT tax would have different effect on fuel costs for different vehicles. For example, a household has two vehicles, a car and a SUV. Suppose the car has a MPG of 30 and the SUV has a MPG of 15 and the gasoline price is $3.00 per gallon, which includes 30 cents of gasoline tax. Now the government decides that instead of charging the per gallon gasoline tax, the household needs to pay a VMT tax that depends on the miles driven of each vehicle and the rate is set at 1.5 cents per mile. Under this new tax mechanism, to drive 30 miles using the small car, the household will pay 3-0.3+0.015*30 = $3.15, compared to $3.00 under the gasoline tax. And to drive 15 miles using the SUV, the household will pay 3-0.3+0.015*15 = $2.925, while the cost would also be $3.00 under the gasoline tax. Therefore, now the equivalent per gallon gasoline cost increases for using the car and decreases for using the SUV and such changes in driving costs would change their vehicle usages of each vehicle. The new annual VMT times the VMT tax rate is the VMT tax revenue. Using the estimates I obtained from model specification (5), I solved for a VMT tax rate in each state so, the total VMT tax revenue would be the same as the current gasoline tax revenue.

Table 5.5 lists the VMT tax rates determined for each state replacing the federal and state gasoline taxes. The highest VMT tax is 2.344 cents per mile in West Virginia and the lowest is 1.221 cents per mile in Georgia.

Table 5.5. VMT tax rates that replacing the 2009 gas tax in each state.

State	2009 State gas tax (cent per gallon)	2009 State & Federal gas tax (cent per gallon)	VMT tax (cent per mile)
AL	18	36.4	1.617
AR	18	36.4	1.982
AZ	21.5	39.9	1.600
CA	18	36.4	1.609
CO	22	40.4	1.680
CT	25	43.4	1.757
DE	23	41.4	1.848
FL	15.6	34	1.599
GA	7.5	25.9	1.221
IA	25	43.4	1.654
ID	19	37.4	1.780
IL	18	36.4	1.653
IN	21	39.4	1.592
KS	24	42.4	1.870
KY	22.5	40.9	1.985
LA	20	38.4	2.003
MA	28.4	46.8	1.737
MD	23.5	41.9	1.779
ME	21	39.4	2.118
MI	19	37.4	1.783
MN	22.5	40.9	1.941
MO	18.4	36.8	1.501
MS	17	35.4	2.200
MT	27.75	46.15	1.968
NC	26	44.4	2.202
ND	24	42.4	1.842
NE	19.6	38	1.861
NH	10.5	28.9	1.727
NJ	18.875	37.275	1.262
NM	24.45	42.85	1.554
NV	30.15	48.55	1.779
NY	23	41.4	1.886
OH	28	46.4	2.118
OK	17	35.4	1.633
OR	24	42.4	1.566
PA	30	48.4	1.877
RI	30	48.4	2.207
SC	16	34.4	1.628
SD	22	40.4	1.767
TN	20	38.4	1.787
TX	20	38.4	1.898
UT	24.5	42.9	1.772
VA	21	39.4	1.543
VT	17.5	35.9	1.731
WA	37.5	55.9	2.077
WI	32.2	50.6	2.208
WV	30.9	49.3	2.344
WY	14	32.4	1.474

Compared to the current gasoline tax rate, the overall miles traveled would slightly decrease and total gasoline consumption would slightly increase. The mean annual VMT per vehicle is 10,028 miles in my final sample and the mean gasoline consumption is 454.73 gallons per year. Under the new VMT tax, the mean annual VMT per vehicle would drop 0.11 percent to 10,016 miles and the mean gasoline consumption would increase by 0.71 percent to 457.95 gallons. Such changes happen because efficient vehicles would face an increased fuel cost under a VMT tax while low MPG vehicles would face a decreased fuel cost. This change would also affect households differently given their vehicle choices. High income households normally own more than one vehicle

Table 5.6. Tax burden changes in various income groups under VMT tax.

Household income	Mean annual gasoline tax burden	Mean annual VMT tax burden	Mean change in tax burden	Percentage change
under 5000	154.02	158.05	4.02	2.61%
5000-9999	135.31	140.86	5.55	4.10%
10000-14999	143.93	150.83	6.90	4.79%
15000-19999	167.15	174.76	7.61	4.55%
20000-24999	194.01	199.48	5.47	2.82%
25000-29999	221.70	225.96	4.26	1.92%
30000-34999	251.14	254.80	3.66	1.46%
35000-39999	273.11	275.26	2.15	0.79%
40000-44999	296.70	296.27	-0.43	-0.15%
45000-49999	310.95	313.00	2.05	0.66%
50000-54999	340.11	343.53	3.42	1.01%
55000-59999	355.65	356.65	1.00	0.28%
60000-64999	379.89	381.37	1.48	0.39%
65000-69999	385.13	384.94	-0.19	-0.05%
70000-74999	408.94	405.79	-3.15	-0.77%
75000-79999	417.01	415.18	-1.84	-0.44%
80000-99999	451.42	449.92	-1.50	-0.33%
above 100000	491.37	484.91	-6.45	-1.31%

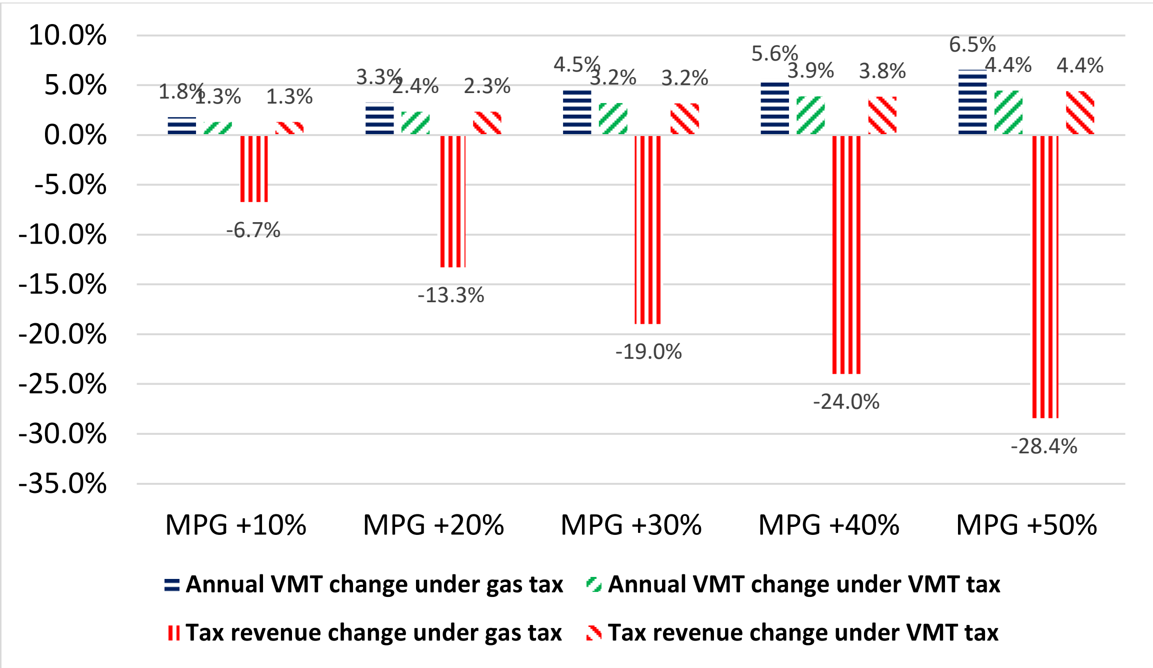
Note: Tax burdens are all in 2009 dollars.

while low income households are more likely to be single vehicle households and own cars with high MPG. As discussed in earlier sections, single vehicle households have a relatively inelastic driving demand when facing driving cost changes. In table 5.6 above, I compared the changes of the average tax burden across various income groups under a VMT tax. My simulation suggested that low income households would bear a heavier tax burden and high income households would pay slightly less tax. Thus, the uniform VMT tax is more regressive than the gasoline tax. However, the magnitude of the average changes are small both in absolute value and percentages. Overall, changing the gasoline tax into a VMT tax would not change people's behavior dramatically in the short run.

VMT tax versus gasoline tax under fleet fuel economy increases

One of the major concern of the current gasoline tax is that the United States is pushing for much more stringent CAFE standards, which aim to almost double the MPG rating of new vehicle models by 2025. Such a huge improvement in fuel efficiency would further decrease the gasoline consumption in households and thus decrease the tax revenue collected under a per gallon based gasoline tax. Under both the VMT tax and the gasoline tax, increases in the overall fuel economy would decrease per mile driving cost and trigger the rebound effect, thus increase vehicle usage. For example, a small car has a fuel economy of 30 and the gasoline price the household face is $3.00 per gallon including 30 cents of gasoline tax. Driving 30 miles would cost the household $3 in fuel. If the fuel economy of the car increased by 25 percent to 37.5, then driving 30 miles would only cost $2.4. Therefore, in the long run, the increase in fuel economy is equivalent to a decrease in fuel cost for the households. However, under the VMT tax, only the pre-tax fuel cost is affected when fuel economy increases. In fact, if household drives more as fuel economy improves, they would pay even more in VMT tax. But households would pay less gasoline tax because of the drop in gasoline consumption.

Figure 5.1. Percentage changes of VMT and tax revenue under fleet MPG changes



Note: The baseline is the gasoline tax revenue and total vehicle usage in the 2009 NHTS data sample. All percentage changes reflect changes in comparison to the 2009 baseline.

In figure 5.1, I show the changes in tax revenue when the overall fleet fuel economy increases. I simulated five scenarios when the overall fleet fuel economy in the United States increased by 10 percent to 50 percent. In each scenario, I simulated the current gasoline tax mechanism and the uniform VMT tax mechanism using the VMT tax rates identified in the previous section. I assumed the pre-tax gasoline price would remain stable and households would be fully aware of the changes in their actual driving costs under both taxes. My simulations show the driving demand would increase as the efficiency of all vehicles improve. The annual usage of vehicles would increase by 6.5 percent if the overall fuel economy increased by 50 percent under the current gasoline tax. Meanwhile, the gasoline consumption and tax revenue would drop by 28.4 percent. Such a huge amount of tax revenue loss would make it difficult for the government to keep up the maintenance of the public road system. The federal and state governments would have to make major increases in gasoline tax rates to be able to maintain the tax revenue and the U.S. public would not like that. To maintain a stable tax revenue, the government would have to raise the gasoline tax by at least 30 percent as fleet fuel economy improved by 50 percent. Such major increases would face huge resistance and could have big impacts in other areas, such as commodity prices.

On the other hand, if a VMT tax was implemented, when fuel economy increased by 50 percent, as intended by the CAFE standards, the usage of vehicles would also increase by 4.4 percent and the tax revenue would increase in par with the change in driving. The tax revenue could reflect the changes in road usage without having to make major adjustment in tax rates as fleet fuel economy improves. This is the biggest advantage of the VMT tax over the current gasoline tax.

Stability under pre-tax gasoline price fluctuations

Next I tested whether a VMT tax would respond differently to pre-tax gasoline price fluctuation and thus face unexpected problems when the global oil price fluctuates for various reasons. I simulated the different scenarios of pre-tax gasoline price changes from -50 percent to +100 percent and compared the vehicle usages and tax revenue collected under the gasoline tax and the VMT tax.

Table 5.7. Tax revenue under pre-tax gasoline price fluctuation.

Pre-tax gas price change		Gas Tax	VMT Tax	Percentage change
0%	Mean Annual VMT	10028	10016	-0.11%
	Mean gas consumption per vehicle	454.73	457.95	0.71%
	Mean tax burden per vehicle	173.46	173.46	0.00%
-20%	Mean Annual VMT	10372	10361	-0.11%
	Mean gas consumption per vehicle	473.56	473.60	0.01%
	Mean tax burden per vehicle	180.80	179.39	-0.78%
-50%	Mean Annual VMT	10888	10877	-0.10%
	Mean gas consumption per vehicle	497.04	497.08	0.01%
	Mean tax burden per vehicle	189.73	188.29	-0.76%
+20%	Mean Annual VMT	9684	9672	-0.12%
	Mean gas consumption per vehicle	442.26	442.30	0.01%
	Mean tax burden per vehicle	168.89	167.54	-0.80%
+50%	Mean Annual VMT	9167	9156	-0.12%
	Mean gas consumption per vehicle	418.78	418.82	0.01%
	Mean tax burden per vehicle	159.96	158.64	-0.83%
+100%	Mean Annual VMT	8307	8296	-0.14%
	Mean gas consumption per vehicle	379.65	379.69	0.01%
	Mean tax burden per vehicle	145.08	143.82	-0.87%

Note: VMT are all in miles per year. Gasoline consumptions are all in gallons. Tax burdens are all in 2009 dollars.

Table 5.7 reports the simulation results and compares the average annual vehicle usage, gasoline consumption and average tax payment per vehicle under various changes in pre-tax gasoline prices. Under all circumstances, gasoline price fluctuation does not impose obvious difference between the two types of taxes. The VMT tax revenue would be slightly less than the gasoline tax revenue when the pre-tax gasoline price fluctuates but the differences would be less than 1% in all tested cases.

Optimal gasoline tax

Previous simulations showed that a VMT tax is capable of providing a more reliable tax revenue flow as vehicles efficiency continues to increase. As explained in the literature review section, gasoline tax rates in the United States are much lower than the optimal gasoline tax rate that can properly integrate all externalities of driving, including pollutions, accidents, and congestions. Therefore, in this section, I explored how driving and the tax revenue would be affected under the optimal gasoline tax, which was calculated as $1.01 per gallon by Parry and Small (2005). I replaced all federal and state tax with the 1.01 per gallon optimal gasoline tax in all states and then simulated the tax burden of this tax. Table 5.8 reports the simulation result at the national level. Total annual vehicle usage would decrease by 4 percent and gasoline consumption would decrease by 3.3 percent. However, the tax burden on households would increase by over 150 percent.

Table 5.8. Overall change under optimal gasoline tax.

	Gas Tax	Optimal Gas Tax	Percentage change
Mean Annual VMT	10028	9625	-4.015%
Mean gas consumption per vehicle	454.73	439.58	-3.332%
Mean tax burden per vehicle	173.46	443.98	155.946%

Note: VMT are all in miles per year. Gasoline consumptions are all in gallons. Tax burdens are all in 2009 dollars.

Table 5.9 shows the simulation results broken down in different income groups. All income groups would be affected severely should the optimal gasoline tax be implemented. Even the low income households would have to pay hundreds extra tax money every year. Although the increase in tax expenditure is quite uniform in percentage among households with different levels of income, living standards of low income households would be affected more because the extra burden takes a larger part in their income.

Table 5.9. Tax burden change in various income groups under optimal gas tax.

	Mean annual household gas tax burden	Mean annual household optimal tax burden	Mean change	Percentage change
under 5000	154.02	391.51	237.48	154%
5000-9999	135.31	341.76	206.45	153%
10000-14999	143.93	367.10	223.16	155%
15000-19999	167.15	428.52	261.37	156%
20000-24999	194.01	491.96	297.95	154%
25000-29999	221.70	563.96	342.26	154%
30000-34999	251.14	645.58	394.44	157%
35000-39999	273.11	695.60	422.49	155%
40000-44999	296.70	749.14	452.44	152%
45000-49999	310.95	796.83	485.88	156%
50000-54999	340.11	871.58	531.47	156%
55000-59999	355.65	907.84	552.19	155%
60000-64999	379.89	978.45	598.56	158%
65000-69999	385.13	988.31	603.18	157%
70000-74999	408.94	1042.57	633.63	155%
75000-79999	417.01	1069.14	652.12	156%
80000-99999	451.42	1163.26	711.84	158%
above 100000	491.37	1260.73	769.36	157%

Note: Tax burdens are all in 2009 dollars.

Discussion

Households choose different types of vehicles based on various things and one of the key factors is their purpose for driving. They respond to driving cost changes differently based on their traveling purposes and the alternatives they have. Using the 2009 NHTS data, I found that driving demands in single vehicle households are relatively more inelastic than that of multiple vehicle households. Also, vehicle usage is more elastic for those used more often for recreational or leisure purposes, such as vans and SUVs. Driving demands of vehicles more often used for daily commute, such as small cars, are relatively more inelastic. Also, in households with multiple vehicles, vehicle usages are more elastic than single vehicle households.

Compared to the current gasoline tax, my simulations showed that a VMT tax would be more regressive than the current gasoline tax. However, the magnitude of the extra tax burden placed on low income households is small (in the vicinity of $5-$6 annually). The benefit of adopting a VMT tax is that it would provide a much more stable tax revenue without having to make major adjustments in tax rates when fleet fuel economy continually increases sharply in response to the stringent CAFE standards. Although a major increase in gasoline tax is politically infeasible in the US, the VMT tax appears to be a better tool not only to stabilize the funding of road maintenance but it also better reflects the true cost of driving as fleet fuel economy increases. The per gallon based gasoline tax could be a good tool in pricing the pollution externality. However, as shown in the simulations, when fuel economy increases, it fails to keep internalizing other externalities of driving that are based on road usage instead of gasoline consumptions. On the other hand, The VMT tax can solve the highway fund shortage in the long run and can better internalize the true driving cost in the US.

The implementation of a VMT tax, especially the transition costs and other concerns, such as privacy, is still in debate. Also, the transition would involve a large initial expenditure in equipment installation cost, which is a big concern. In addition, during the transition period, with both the VMT tax and the gasoline tax in place, the cost of tax collection would be much higher. Furthermore, people's short run responses to the new tax could be surprising. For example, in Oregon's pilot program, average vehicle usage actually went up although participants were spending more on driving costs. Officials concluded this was because participants were paying less at the pump because they were no longer paying gasoline tax and the monthly VMT tax bills were somewhat less connected to their driving behavior compared to the traditional pay at the pump gasoline tax. Therefore, there is still a lot to learn to accurately calculate the transition costs. Regardless of these concerns about execution in the short run, VMT tax appears to be a viable alternative for gasoline tax should we want to further improve the overall fuel economy.

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CHAPTER 6

CONCLUSION

The CAFE standard is a symbolic performance based regulation. It sets standards on a particular attribute of a publicly sold product and leaves enough flexibility for producers to comply with the regulation in various ways. Four decades have passed since CAFE standards were first enacted. Consumers, automakers, and governments at various levels are now facing impacts that might not have been foreseeable when the CAFE standards were introduced. In this thesis, I looked into the impacts of this important regulation from different angles and made an attempt to predict its future impact as well as possible actions the government could take to mitigate some of the foreseeable negative impacts.

In chapters two and three, I studied the historical data of the attributes of vehicle models sold and thus regulated by CAFE standards in the U.S. market. The regulated industry appeared to have been resourceful in complying but CAFE standards did succeed in forcing firms to shift their priorities in the direction that the government intended for. Proven to be effective tools, CAFE standards were further tightened by the

U.S. government in the upcoming decade to reduce greenhouse gas emission. Admittedly, firms were clearly facing pressure to find a balance between complying with the standards and providing the larger and more powerful vehicles that consumers preferred. World famous firms, including Volkswagen and Mitsubishi, had been caught cheating in emission tests or fuel economy tests. These events, however, should not be seen as signs that firms have already reached their limits in innovation. Vehicle models that have new technology installed still keep showing up on the market every year. If firms behave in a manner similar to what they have in the past when CAFE standards were tightened sharply, my predictions suggest that we would only see a small or moderate decrease in the weight and engine power of upcoming new vehicle models on the market. Also, as the market share of vehicles using new technologies, such as the hybrid vehicles and the electric vehicles, increases, the pressure to downsize vehicles will likely be less severe than it first seemed. Therefore, we do not need to be too concerned that the new aggressive CAFE standards will make the new cars less safe on the road. In fact, I modeled the technological innovation in the automobile industry and showed that the tightening of the stringency of CAFE standards had pushed up the innovation rate in fuel economy related technologies. CAFE standards do not just help in emission control but have also served as an innovation driver. Firms made more improvements in fuel economy related innovation when CAFE standards were increasing sharply compared to when CAFE standards remained stable. If we believe that fuel efficiency is important for our future, then more stringent performance standards, such as CAFE standards could definitely accelerate the innovation in the desired direction.

Though the CAFE standard only regulates automakers, it has also had profound influences outside the industry. The fuel economy of vehicles has greatly improved in the past few decades, which is exactly what CAFE standards were designed to do. However, while these changes reduced the gasoline consumption in the US, they also reduced the gasoline tax revenue. In chapter four and five, I studied the household survey data and simulated how the tax revenue would further drop as overall fleet fuel economy further improves. My simulations also show that a VMT tax, which would tax people based on the distance they drive instead of on their gasoline consumption, would remove this negative financial impact of CAFE standards. The VMT tax has previously been criticized for putting privacy into risk and providing negative incentives for using efficient vehicles. However, my study showed that if we take into account that vehicles are getting more efficient, the VMT tax would actually be a better tool, not just in providing more stable tax revenue, but also in pricing the cost of driving. Raising the gasoline tax had been considered as the best approach for pricing the cost of driving in previous studies because it prices pollution, which is the major externality of driving, directly. However, as fleet fuel economy increases, the cost of pollution would take smaller part in the total externalities of driving, while the cost of congestion and accidents become more important. These externalities are all directly related to the usage of roads, which is what a VMT tax is based on. There could be high transition costs in the short run if the government decided to replace the gasoline tax with the VMT tax. But in the long run, the VMT tax could serve as an effective tool to mitigate the negative impacts of a stringent CAFE standard and to better internalize the cost of driving in the US.

As a milestone performance based regulation, the CAFE standard has been controversial in the past. My thesis looks into its impacts and introduced tools to predict its future impacts as the stringency of the regulation changes. These methods can be applied to performance base regulations in other industries. I also discussed the benefit of a VMT tax that could mitigate the long term effect of CAFE standards on the transportation sector. My simulation methods and results could be useful references for policy makers in designing future tax structures to better manage road usage in the US.

APPENDIX

DATA CONSTRUCTION OF THE 2009 NHTS DATA

In what follows I provide an overview of each of the data I used in chapter four and five and discuss the construction of the sample used in the analysis and provide detailed cleaning procedures and detail the precise construction of several of the key variables.

I. Data summary and construction of the household vehicle sample

For several decades, the US DOT Federal Highway Administration (FHWA) has conducted the National Personal Transportation Survey (NPTS) with two most recent surveys occurring in 1990 and 1995. In more recent years, the NPTS was supplanted by the more comprehensive National Household Transportation Survey, which has been conducted twice in 2001 and 2009. The NHTS/NPTS data include information on travel demand as well as socio-demographic for sampled households. A RDD sampling procedure was used to initially select the national sample of household participants, as well to conduct follow-up household and personal phone surveys for the national sample. In addition, since the 1990 NPTS, additional 'add-on' surveys were conducted in certain regions by request. The publicly available NHTS data of 2009 contains 3 major files, the household file, which records household information and regional information, the individual file, which records information of individual household members, and the vehicle file, which records individual vehicles. There are a total of 25,510 national households and 124,637 add-on program households recorded in the published 2009 NHTS data.

Households that claim to own vehicles were also asked to provide information of their vehicles and the usage of each vehicle. Vehicle type, vehicle make, vehicle model, and vehicle model year are reported using the US DOT National Highway Traffic Safety Administration coding system in the NHTS data. Using the NHTSA codes, I merged additional vehicle attribute information that were primarily collected from WAY, which includes data for mode years 1971-2011, and which was supplemented with information from the AC, which includes attribute data for model years 1945-2013. A detailed discussion of these data, including their advantages and disadvantages, is provided in Section II below.[27] Despite my best efforts, in some cases I was unable to match some of the vehicles in the 2009 NHTS data with the WAY and AC datasets because of missing or incorrectly coded vehicle make, model, and/or year. I managed to match 91.9 percent of the vehicles in the 2009 NHTS data with vehicle attribute data.

Next I discuss the edits I performed to the NHTS data to construct the sample. I made four waves of edits in data merging. These changes to the sample were tracked across two dimensions, households and vehicles. The first edit I performed was to handle unmatched vehicles, which as I lack vehicle attribute data for these vehicles, could not be used in my analysis. I adopted a conservative approach that attempts to save as many

[27] I focus my analysis on passenger vehicles, which include two categories, passenger cars with NHTSA model codes from 1-399 and light duty trucks with model codes from 401-699. Motorcycles, farm vehicles, recreation vehicles, commercial trucks and other unknown vehicles are all excluded from the analysis.

households as possible without potentially biasing my analysis. First, I dropped households that had unmatched vehicles with missing or implausible adjusted annual VMT[28] (i.e. annual adjusted VMT that is fewer than 100 miles or greater than 60,000 miles). These households were dropped because their VMT information were unreliable. What remained after this cut were households with plausible VMT information (e.g. VMT greater than 101 miles and less than 60,000 miles), including households where the unmatched vehicles corresponded to a large proportion of household VMT. The unmatched vehicles that are frequently used could bias the results and thus I dropped households that have unmatched vehicles with VMT between 1,001 and 60,000 miles. For the remaining subset of households that have unmatched vehicles with VMT between 100 and 1,000 miles, which suggested that the unmatched vehicle was not the principal vehicle used by the household, I removed the vehicle but keep the household. As shown in Table I, removal one of households, this corresponds to the removal of 15,764 households. In addition, as shown in removal one of vehicles, I removed 21,334 vehicles. Out of the removed vehicles, 2,947 vehicles had VMT between 100 and 1,000 miles and the household was kept.

The final three edits applied to all households and reflect the case where key vehicle information were unreliable or missing. As for unmatched vehicles, I also dropped households that had matched vehicles with adjusted annual VMT that were either missing or implausible (e.g. adjusted annual VMT that is less than 100 miles or more than 60,000 miles). This corresponds to the removal 5,493 households (removal two in row four). Second, I dropped the household if it reported an average annual VMT

[28] The construction of annual VMT will be discussed in detail in the variable construction section.

per driver in excess of 60,000 miles. Annual VMT per driver is simply the sum of the adjusted annual VMT of all passenger vehicles that are kept in each household divided by the reported number of drivers in the household. This corresponded to the removal of 77 households (removal three in row five). After applying these edits, the constructed sample contains 128,811 households and 224,326 vehicles.

Table I. 2009 NHTS sample construction steps.

Households	
Total number of households in starting sample	150147
Total households removed	-21336
Removal one	-15764
Removal two	-5493
Removal three	-77
Removal four	-2
Total removals as % of starting sample	-14.2%
Total number of households in constructed sample	128811
Vehicles	
Total number of passenger vehicles before removals	279783
Total vehicles removed	-55452
Removal one	-41881
Removals from dropped households	-39539
Removals from kept households	-2342
Removal two	-13341
Removal three	-235
Total removals as % of final sample before removals	19.8%
Total number of vehicles in constructed sample	224326

In my thesis, I further removed households that did not own vehicle and observations that had missing information in socio-demographic variables from the constructed sample. These observations could not be used in the regression analysis in chapter four and five. The final sample contains 207,382 vehicles and 94,645 households.

II. Variable Construction

Vehicle miles travelled

Annual Vehicle Miles Travelled (VMT) is a key variable in my analysis. I used the self-reported annual VMT ("annmiles") from the NHTS data. I considered the VMT numbers implausible if self-reported VMT was fewer than 100 miles or greater than 60,000 miles. I used the alternative estimates of VMT reported in the 2009 NHTS data if the self-reported VMT was missing or implausible. In these instances, I used the "bestmile" variable reported the data instead of the self-reported VMT. The "bestmile" variable was constructed by Oak Ridge National Laboratory (ORNL) using available information in the surveys such as household travel behavior and odometer readings. The final combined variable is the adjusted annual VMT. As stated in the previous section, households were dropped if the adjusted annual VMT was also implausible given the same criterion provided here.

Household income

I used the median of each income category that is not top coded, for example, $7,500 for households with income reported as between $5,000-$9,999. For top coded income households, I used the boundary, which was $100,000 in 2009 NHTS. These values were used to run statistics in data validation. I treated income as a categorical variable in my analysis in chapter four and five.

Race of household respondent

The 2009 NHTS recorded the race of household respondents into eight categories. To provide more consistent comparisons with other studies, I collapsed race into four categories, white, black, Asian, and other races.

Miles per gallon (MPG)

Fuel economy is also a key variable in my analysis. As discussed in chapter four, I first adjusted the MPG rating in the AC data and the WAY data so that they were comparable to each other. I then merged the combined vehicle attribute data and match the vehicle models with individual vehicles reported in the 2009 NHTS data.

III. Sample Validation

In this section, I performed a comprehensive comparison of the constructed sample. Tables II through VIII compared the socio-demographics and vehicle summary statistics between households kept and households dropped.

Table II. Vehicle composition comparison.

	Kept	Dropped
Total number of households	128,811	21,336
Total passenger vehicles	224,326	52,510
Total number of cars	114,526	29,745
% of passenger vehicles	51.05%	56.65%
Total number of light trucks	109,800	22,765
% of passenger vehicles	48.95%	43.35%

	T-score
Cars	17.31
Light trucks	-15.47

Table III. Comparison of vehicle composition.

	Kept	Dropped
Total Number of Households	128,811	21,336
Total Matched Passenger Vehicles	224,326	32,850
Total Small/Medium Cars	93,319	12,680
% of matched passenger vehicles	41.60%	38.60%
Total Large Cars	21,207	2,891
% of total passenger vehicles	9.45%	8.80%
Total Pickups/Vans	61,764	10,170
% of matched passenger vehicles	27.53%	30.96%
SUV/CUV	48,036	7,109
% of matched passenger vehicles	21.41%	21.64%

	T-score
Small/medium cars	-6.5
Large cars	-1.16
Pickups/vans	6.95
SUV/CUV	0.44

Tables II and III compare the average composition of the passenger vehicle fleet for households kept and households dropped. As shown in Table II, the percentage of cars to all passenger vehicles is lower in households kept than in households dropped in the 2009 NHTS (51.1 percent versus 56.6 percent). These differences are statistically significant at 5 percent level.

In Table III, I compared various vehicle categories for passenger vehicles that were successfully matched to the WAY and AC datasets. There are statistically significant differences at the 5 percent level in small/medium cars, with more small/medium cars in the kept than the dropped samples. Likewise, pickups and vans are overrepresented in the dropped households.

Table IV. Comparison of VMT, MPG, and income between households.

	Kept	Dropped
Total number of households	128,811	21,336
Total vehicles with valid VMT	224,326	45,267
Mean VMT	9,905	10,275
Std.	8159	9053
Total vehicles with MPG	224,136	32,776
Mean MPG	23.1	22.5
Std.	5.5	5.5
Total households with income	118,600	19,338
Mean Income	55,163	58,449
Std.	31,968	31,776

	T-score
VMT	0.03
MPG	-0.074
Income	0.073

Table IV compares the adjusted annual VMT, MPG, and imputed household income for both kept and dropped households. T-tests show that there is no significant difference between households kept and households dropped in all these variables. As these variables are central to my analysis, the finding of no statistically significant difference between samples for these variables is critical.

Table V. Comparison of sex, age and race of household respondents.

	Kept	Dropped
Total number of households	128,811	21,336
Male household respondent	51,176	6,550
% male household respondent	39.70%	30.70%
Female household respondent	76,901	12,929
% female household respondent	59.70%	60.60%
Sex unknown	734	1,857
Mean age of household respondent	58.7	56.7
Std.	15.5	15.6
Age unknown	734	1,857
White household respondent	110,391	16,481
% of white household respondent	85.70%	77.20%
Black household respondent	7,904	1,233
% of black household respondent	6.10%	5.80%
Asian household respondent	2,414	339
% of Asian household respondent	1.90%	1.60%
Other races	8,102	3,283
% of other race household respondent	6.30%	15.40%
Race unknown	0	0

	T-score
Male household respondent	-14.82
Female household respondent	1.94
Age of household respondent	0.06
White household respondent	-24.64
Black household respondent	-0.5
Asian household respondent	-0.39
Other race household respondent	13.28

Table V compares the age, gender, and race of the household respondent between households dropped and households kept. The t-tests show that in the 2009 NHTS, there are significantly fewer male household respondents in dropped households (30.7 percent compared to 39.7 percent in kept households). I found no significant difference in age of household respondent. In the race comparison, I found significantly fewer white household respondents in households dropped (43.4 percent versus 48.9 percent in households kept). Also, in the 2009 NHTS, 'other' races are significantly greater in dropped households (15.4 percent versus 6.3 percent in kept households).

Table VI. Comparison of highest education in households.

	Kept	Dropped
Total number of households	128,811	21,336
Less than high school	6,976	1,227
% less than high school	5.40%	5.80%
High school	27,369	4,644
% high school	21.20%	21.80%
Some college	35,933	6,188
% Some college	27.90%	29.00%
Bachelor	29,892	4,927
% Bachelor	23.20%	23.10%
Graduate school or more	28,331	4,258
% graduate school or more	22.00%	20.00%
Education unknown	310	92

	T-score
Less than high school	0.47
High school	0.8
Some college	1.76
Bachelor	-0.17
Graduate school or more	-3.08

Table VI compares the highest education level attained by any member of a household between dropped and kept households. T-tests suggest that there were fewer households with highest education level attained being “graduate school or more” in households dropped in the 2009 NHTS (20 percent versus 22 percent in households kept). In these cases the differences are not substantial in magnitude, although they are statistically significant at the 5 percent level.

Table VII. Summary statistics of life cycle in households.

	Kept	Dropped
Total number of households	128,811	21,336
1 adult no child	14,095	1,043
% of 1 adult no child	10.90%	4.90%
2+ adult no child	25,981	5,494
% of 2+ adult no child	20.20%	25.80%
1 adult youngest child age 0-5	554	56
% of 1 adult youngest child age 0-5	0.40%	0.30%
2+ adult youngest child age 0-5	10,666	2,271
% of 2+ adult youngest child age 0-5	8.30%	10.60%
1 adult youngest child age 6-15	1,869	168
% of 1 adult youngest child age 6-15	1.50%	0.80%
2+ adult youngest child age 6-15	13,827	2,999
% of 2+ adult youngest child age 6-15	10.70%	14.10%
1 adult youngest child age 16-21	995	144
% of 1 adult youngest child age 16-21	0.80%	0.70%
2+ adult youngest child age 16-21	5,162	1,464
% of 2+ adult youngest child age 16-21	4.00%	6.90%
1 retired adult no child	19,189	1,324
% of 1 retired adult no child	14.90%	6.20%
2+ retired adult no child	36,473	6,373
% of 2+ retired adult no child	28.30%	29.90%
Unknown	0	0

Table VII compares the life cycle of households for dropped and kept households. Table VIII compares the number of children, seniors, and workers in the household. In both tables, the standard deviations are so large for all comparisons that there is no necessity to report the t-test statistics as I found no meaningful difference between dropped and kept households in most variables.

Table VIII. Summary statistics of number of children, seniors and workers.

	Kept	Dropped
Total number of households	128,811	21,336
Number of Children Aged 5-16	0.27	0.32
Std.	0.68	0.74
Number of Children Aged 17-21	0.07	0.11
Std.	0.29	0.36
Number of workers	0.9	1.06
Std.	0.88	0.93
Number of seniors (>=65)	0.58	0.51
Std.	0.75	0.74

IV. Merging in Vehicle Attributes Data

As discussed in Section II, both the WAY and AC datasets have advantages and disadvantages. For the purpose of my studies, the WAY data is preferred to the AC data, except for vehicles before 1979. For each make-model-year reflected in the NHTSA code reported in the NHTS data, I assigned the basic trim from WAY to each vehicle. Basic trim is defined as the trim with the most basic settings in all settings available in a given make-model-year. For example, WAY report two trims of 1997 Acura CL, 2.2 CL and 3.0 CL. I picked 2.2 CL to represent the 1997 Acura CL. In the WAY and the AC data, the basic trim is normally the first trim of the model in each model year, with a less powerful engine and low manufacture suggested retail price (MSRP). When a make-model-year was not available in the WAY data or was missing key information in the WAY dataset, such as MPG, I used data from AC instead.

Vehicle model year was self-reported in the NHTS/NPTS data. In examining the data, it became clear that some households confused the year they purchased their vehicle with the model year of the vehicle. As such, I made adjustments to correct for this error. For households that reported a vehicle as having a model year that was one year preceding the first year the model was offered, I recoded the self-reported model year to the first year the model was offered. For example, the first available model year of the Toyota Venza was 2009. Some households reported having a 2008 Toyota Venza, which were recoded to 2009.

I was also constrained by the way model year was coded for older vehicles in the NHTS data. For example, in the 2009 NHTS, all vehicles with model years prior to 1985 (1923 to 1984) were assigned a model year of 1974. Given that it was more likely for a newer vehicle to survive till the time of the survey, I first assigned these vehicles as being of the 1984 model class. If by 1984, that model had not yet emerged (or had expired), I then assigned that vehicle to the 1983 model class for that model. I repeated this recursively until 1975. I stopped at 1975, which was ten years prior to 1984. I did not go past 1975 because the survival probability for pre 1975 vintage vehicles was very low at 2009.

For light trucks of model year 1991 and before, the model names were often too brief for me to match conclusively. For example, Chevrolet C, K, R, and V-series pickups all shared a single model code of 481 in the NHTSA coding system while there were 16 different models in the WAY and AC data. To recover as much information as possible for the light truck fleet prior to 1992, I attempted a best guess so that I could include these vehicles in the constructed data. Assuming that make-model-year were accurate for these vehicles, I attempted to match the model for these vehicles to other truck attribute data included in the WAY and AC datasets. For example, if a 1971 Ford truck was coded as being an 'unknown light truck', when the WAY and AC data reported that only Ford Broncos was made in that year, I classified the vehicle as being a 1971 Ford Bronco. In another instance, the later year GMC Savana truck shared the same NHTSA code as the earlier year GMC Vandura. Consequently, given the appropriate NHTSA codes and reported model year, I assigned the truck as being a Savana or a Vandura.